UNIVERSITÀ DEGLI STUDI DI PADOVA

Dipartimento di Psicologia Generale

Corso di Laurea Magistrale in Neuroscienze e Riabilitazione Neuropsicologica

L'effetto del feedback sul compito di apprendimento motorio nei pianisti

The feedback' s effect on motor learning task in pianist

Relatore

Prof.ssa Giorgia Cona

Laureanda

Caterina Tagliavini

Matricola 2023843

Anno Accademico 2022-2023

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Contents

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Abstract

Our project's aim is to investigate the impact of feedback in both behavioural results and neurocorrelates. The goal is to see if pianists will learn faster with negative feedback during a music performance related to a motor learning task. Additionally, we want to investigate if this accelerated learning rate with negative feedback is mediated by decreased beta oscillations.

In other words, in terms of behavioural outcomes, our hypothesis assumed that pianists would learn faster, this means they will adapt their actions more quickly, with negative feedback than positive feedback. In terms of neurocorrelates, we hypothesized that the accelerated learning rate during negative feedback processing is mediated by reduced beta oscillations.

For the expected results, this current study will attempt to explain the relationship between feedback, motor learning, and beta oscillations. We will face the anxiety topic since it is strongly connected with motor learning and beta oscillations.

Since humans constantly use feedback, whether implicit or explicit, to adapt their movements or future choices, we must first understand the strong relationship between feedback and motor learning. Our study will first focus on what feedback is, then how different types of feedback are related to different learning rate outcomes and how feedback are associated with motor learning. As a result, the first two chapters will attempt to explain those topics. Consequently, we will discuss the connections between musicians and anxiety symptoms, as well as why this is an important topic. Indeed, this study is highly interests in anxiety symptoms and how they affect future behaviour and thus decision-making processes. Overall, data suggest that anxious people are more likely to change their behaviour in response to negative outcomes (Aylward et al., 2019). Finally, we'll go over how beta oscillations change during the learning process. To better understand the relationship between those topics, we will use a previous experiment as an example. Following our discussion of these topics, we will move on to our experiment research.

Chapter 1: The role of Feedback

1.1 Feedback processing

Feedback can be conceptualized as the outcome, the result, of an action captured by the senses (Luft et al., 2014). As a result, the outcomes must be perceptible, such as hearing verbal feedback, or observing the outcome of an action (Luft, 2014). This can be expressed by an external source, such as an audience, or by an internal source, such as the motor outcome of a specific action.

Individuals use feedback to monitor or improve their skills and learn from them, which includes updating their beliefs about the consequences of an action based on the feedback they receive (Coffman, Araya, & Zafar, 2021).

The underpinning model based on this concept is Bayesian inference, in which more information is used to update the probability of a hypothesis (Stone, 2013). For instance, after performing a particular action and receiving feedback, the individual would obtain additional information. These additional knowledges and updated beliefs are subsequently employed when the same action is performed again, however, this time it is executed according to the updated beliefs (Coffman, Araya, & Zafar, 2021).

Individual's beliefs and choices are significantly influenced by feedback. It has been shown that individuals revise their beliefs and choices by 0.15 to 0.35 standard deviations (SDs) on average immediately after receiving feedback. Nonetheless, one week later, these revisions have partially faded back to their starting points. However, the impact of bad news appears to fade less over time than the impact of good news.

It is critical to understand that positive and negative feedback have different effects on how people change their beliefs and actions. A key aspect of learning from feedback is the ability to distinguish between positive and negative feedback, which allows individuals to learn whether their action was appropriate and should be repeated, or whether it should be avoided or changed (Huang & Yu, 2014).

How can positive and negative feedback be distinguished?

Positive feedback can be defined as a signal that a task was accomplished correctly, whereas negative feedback can be defined as a signal that a task was performed incorrectly. Positive and negative feedback are both important for improving performance because they signal the continuation or modification of current behaviour (Crone et al., 2004, 2008; Huizinga et al., 2006).

Positive feedback is typically expressed by a reward (correct response) in a reinforcement learning framework, whereas negative feedback is typically expressed by a punishment (in case of errors). Processes such as avoiding punishments or seeking rewards have a strong influence on human behaviour. Both of these processes are influenced by different types of feedback that the individual

has used to determine the next step to take in order to achieve the desired results. Humans require feedback to know where actions are heading and to plan a course correction if the result (outcomes) of the action are not what we expected.

The topic of motor learning will be covered later.

It is necessary to define what is meant by "feedback" and how studies about the feedback processing are important because they are strongly connected with learning processes. Indeed, feedback has been recognized as an essential facilitator of learning and performance (Fedor, 1991; Ilgen, Fisher, & Taylor, 1979). Feedback is beneficial for a variety of reasons. First, feedback that indicates a gap between current and desired levels of performance, or goals, can motivate higher levels of effort (Locke & Latham, 1990). Second, feedback can help to reduce uncertainty about how well one is performing on a task, and one is either performing rather well or poorly on a task (Ashford, 1986; Ashford & Cummings, 1983). g either well or poorly on a task (Ashford, 1986; Ashford & Cummings, 1983). Reduced uncertainty may lead to higher motivation and more efficient task strategies, the reason behind this is because uncertainty is often unpleasant and can divert attentional resources away from task performance (Kanfer & Ackerman, 1989). Third, feedback provides information that can be used to correct inappropriate task strategies (Ilgen et al., 1979), especially when the feedback is more specific (Baron, 1988; Goldstein, Emanuel, & Howell, 1968; Goodman & Wood, in press; Wentling, 1973).

Humans make different decisions based on the type of feedback they receive. If it is true that feedback significantly change individuals' beliefs and choices, then they have a significant impact on the direction of future decisions.

Recent research (Schiffer, A., et al., 2017) has looked into what happens in the brain after receiving feedback. Most of these studies focused on the event related potentials (ERPs), especially on a component called the feedback related negativity (FRN).
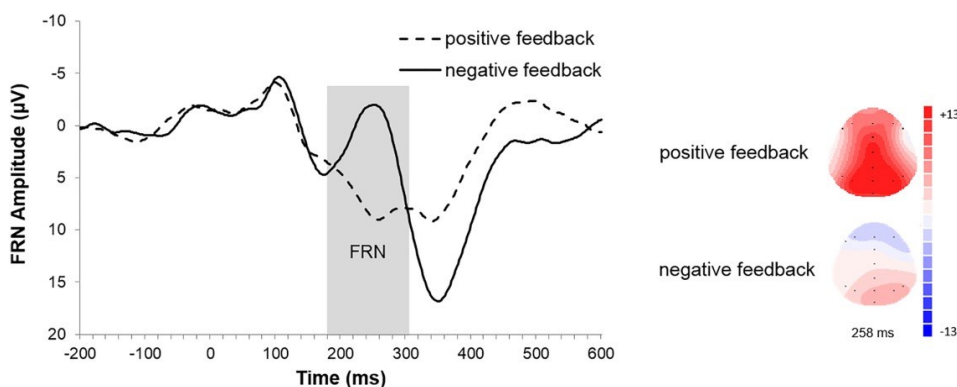
Figure 1, FRN amplitudes is larger to negative feedback than to positive feedback.

It has been investigated the FRN as an index of the performance monitoring system activity in response to feedback. FRN is a negative deflection in the ERPs that occurs in response to feedback around 145/300 mms. In a variety of ways, this electrophysiological feature of feedback processing has been linked to learning.

According to studies (Schiffer et al., 2017), a higher FRN is associated with a higher likelihood of performance corrections or adjustments. As according to research, learning results in a lower FRN in response to negative feedback because the prediction error is reduced when people already know the action and outcome associations. FRN appeared to be present after both positive and negative feedback was expected, implying that the FRN represents the expectedness of the feedback rather than its valence. People immediately begin to evaluate their previous choices or beliefs after receiving feedback in order to adjust to achieve the desired outcome. These adjustments appear to be more persistent if the feedback was negative; in fact, it has been demonstrated that the adjustments appear to be maintained for a longer period of time than when the feedback received was positive. The impact of bad news appears to fade faster than the impact of good news (Coffman et al., 2021). To properly assess how musicians learn from different types of feedback, both negative learning bias and motor learning should be evaluated.

1.2 Negative learning Bias

Learning biases are cognitive biases that lead to selective learning, which is a mechanism that allows individuals to distinguish between essential and irrelevant information (Shabel, Murphy, and Malinow, 2014; Hoang, & Sharpe, 2021). Selective learning is used to focus on important information (Dolguikh, Tracey, & Blair, 2021; Hoang & Sharpe, 2021).

Selective learning occurs when individuals pay selective attention to a specific type of feedback, resulting in a difference in learning outcomes depending on the type of feedback received (Dolguikh et al., 2021).

Individuals who have a negative learning bias are more likely to pay attention to negative feedback. Positive feedback is generally regarded as less important and is not allowed to influence future repetitions of the action. A professional pianist, for instance, who has a negative learning bias while performing will tend to focus on negative feedback rather than any positive feedback. This is known as the negative/positive asymmetry because positive feedback receives less attention than negative feedback (Rozin & Royzman, 2001).

Research studies are still being conducted to determine why feedback processing and feedback adaptation differ between individuals based on the type of feedback, positive vs negative, as some

6

learn faster from negative feedback than others do from positive feedback (Galea, Mallia, Rothwell, & Diedrichsen, 2015).

Galea et al. (2015) and other recent studies established that people generally learn faster when they receive negative feedback.

In general, negative learning biases have been found to be prominent in individual who show anxiety symptoms (MacLeod & Mathews, 2012). Music performance anxiety (MPA) affects approximately 50% of professional musicians. It is an anxiety condition in which musicians experience cognitive and physiological symptoms, such as trembling hands, accelerated heart rate and fear while performing (Fernholz et al., 2019). These cognitive and physiological conditions caused by anxiety traits would impair the motor learning process. Furthermore, this finding suggests that anxiety impacts both the negative learning bias and the motor learning process.

In terms of neural correlates that could support this hypothesis that negative feedback is more likely to be elaborated, it has been discovered that the medial prefrontal cortex (PFC), including the anterior cingulate cortex (ACC) and supplementary motor area (SMA)/preSMA (Rushworth et al., 2004, 2007), and dorsolateral PFC (DLPFC) are frequently found to be more active after the presentation of negative performance feedback in adults (Mars et al., 2005; Zanolie et al., 2008a). Individuals appear to learn more from their mistakes than from their correct choices.
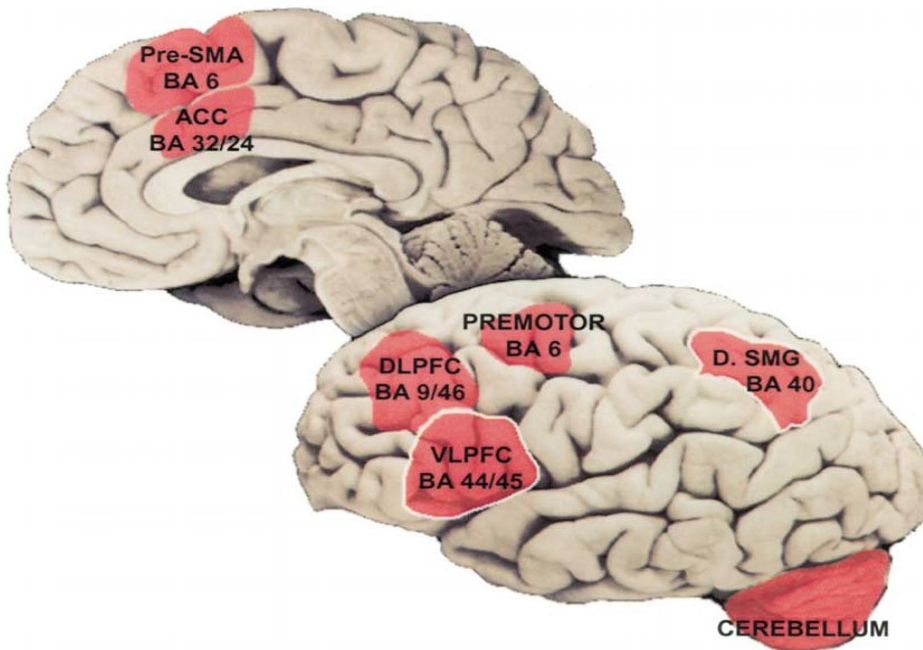
Figure 2, brain areas involved in negative feedback elaboration.

There is a relationship between negative learning bias and anxiety symptoms, they are linked. Indeed, it has been discovered that people who suffer from anxiety do have a negative learning bias (MacLeod & Mathews, 2012).

Recent research has confirmed the presence of bias for selective attention towards negative information, both in people suffering from anxiety disorders and in nonclinical individuals (Bar-Haim et al. 2007). As a result, it demonstrates that the pattern of selective information processing is associated with dysfunctional anxiety. These findings are especially significant for the purposes of this study since, as already said, has been revealed that roughly half of professional musicians suffer from music performance anxiety (MPA), an anxiety condition where musicians experience cognitive and physiological symptoms while facing music performance (Fernholz, Mumm, Plag, et al., 2019).

The manner in which we process feedback has a significant impact on the quality of learning; indeed, feedback plays a critical role in many types of learning. Of particular interest is the comparative effectiveness of positive and negative feedback to learning (Abe et al., 2011; Brackbill & O'Hara, 1957; Frank, Seeberger, & O'Reilly, 2004; Galea et al., 2015; Meyer & Offenbach, 1962; Wächter et al., 2009). Negative feedback appears to be far more effective for

learning in this case. This suggests that the human implicit learning system is capable of learning even when there is no positive feedback.

Chapter 2: Motor learning

2.1 Motor learning process

Humans have an extraordinary learning capacity that allows them to acquire a wide range of skills, from motor actions to complex abstract reasoning.

All of the movements that humans engaged in their daily lives are essential components of our experience as we interact with the world around us. The majority of these movements are taken for granted by the general public. Consider the following: walking, driving a car or brushing our teeth. All of these are movements that most of us do on a daily basis and have learned through trial and error. Other actions, on the other hand, require us to spend more time practising them before we can accomplish our goals. These actions are challenging to learn and demand longer time from us; those actions could be either represented by athletes or performing artist such as dancers or musicians.

Motor learning can be defined as an internal process or state that reflects a person's current ability to produce a specific movement (Schmidt, et al., 2008). Motor learning encompasses a wide range of phenomena, from relatively low-level mechanisms for maintaining our movements calibrated to making high-level cognitive decisions about how to act in a given circumstance (Krakauer et al., 2019).

Motor learning is concerned with making more efficient movements. It could be divided into two parts: skill acquisition, which is the process by which an individual acquires the ability to identify an appropriate movement goal, and skill maintenance, which is the ability to maintain performance level under changing conditions. These two aspects of motor learning are crucial, and they most likely share neural circuitry.

Motor learning has multiple components that interact and influence each other (Wolpert et al., 2011). Information extraction is one of these components. The individual is actively filtering incoming information based on the current action. Decisions represent another essential component. Motor task frequently involve a decision-making process in which, the person must decide when and how to move based on the extracted information. The third component is defined by the action's control. When lifting an object, for example, people scale the lifting force applied by the fingertips in anticipation of the object's weight. Such predictions necessitate the use of a system capable of effectively simulating the behaviour of our bodies and environments.

The cognitive mechanisms required to learn a task are referred as part of the learning process. It is

necessary to differentiate between error-based learning and reinforcement learning, which are both types of learning processes but with distinctive characteristics. According to Wolpert et al., the learning process is defined by the nature of the information used to learn, regardless of sensory modality.

The process of learning through finely graded error information is referred to as error-based learning, whereas in reinforcement learning, the agent uses rewards/punishment in the form of categorical information, such as the relative success or failure of an attempt, to learn.

There are significant differences between these two types of learning processes, both of which deserve to be evaluated.

Consider launching a ball with the goal of hitting a specific target. The outcome of the movement is compared with the predicted error in error-based learning, and by estimating the error gradient, the system knows not only that it missed the target but also how it missed it. As a result, this type of learning necessitates feedback that informs not only that an error occurred, but also how, in which way, the error occurred. In a reinforcement learning framework, on the other hand, an agent learns which actions to take in order to maximize the numerical reward signal through trial and error. The error information is categorical: it informs that a mistake has been made without providing additional feedback about the error information, and without providing any information about the required behavioural change direction. As a direct consequence, the motor system must investigate various options in order to gradually improve the motor commands This feedback is commonly depicted as a reward (correct response), punishment or lack of reward (in case of errors).

Reinforcement learning, like error-based learning, can be used to guide learning towards the solution manifold, but because the signal (the reward or punishment) provides less information than error-based learning, such learning is slower. One critical problem that needs to be solved in reinforcement learning is determining how to assign credit or blame to the actions that resulted in reward or punishment. Learning the associations between action and outcome (reward or punishment) tends to increase an individual's ability to achieve the desired goal.

A reinforcement learning system is made up of four major components: a policy, which is a way of behaving at a specific point in time that corresponds to a set of stimulus-response associations. A reward function, which is a function that represents the intrinsic desirability of a certain state, i.e., what are good and bad events, and serves as the foundation for policy change. A value function reflects how much reward the individual anticipates accruing over time. While the reward function determines what is immediately good or bad, the value function determines the long-term desirability of states. An environment model, the last component, which is a set of action predictions that mimic the behaviour of the environment. This final feature enables the system to

make new predictions and plan ahead in order to avoid making the same mistakes over and over again rather than learning from them.

Thus, motor learning is based on feedback adaptation of sensorimotor processes and actions (Wolpert, Diedrichsen, & Flanagan, 2011). Motor control is employed to organize and control movement, while feedback provides input to adapt movement organization and execution (Cech & Martin, 2012; Wolpert & Flanagan, 2010).

In this viewpoint, feedbacks, regardless of what is being learned, are essential; not only for correcting errors but also for monitoring and enhancing performance all the way to a highly proficient level. As a result, fields related to learning processes have extensively researched feedback processing.

Reinforcement learning is one of the most widely debated learning processes in terms of feedback. As previously stated, in reinforcement learning, the agent uses categorical information to learn a task, such as the relative success (reward) or failure (punishment) of an attempt. How do punishment and reward affect motor learning processes?

One widely held belief is that motor learning is a fundamental mechanism that is unaffected by various types of feedback. In a previous study, Galea and colleagues rejected the hypothesis that motor learning is independent of feedback, demonstrating that different types of feedback affect the learning process. It has been discovered that how negative feedback is processed affects the learning process differently.

As a result, the common assumption regarding motor learning adaptation in which the process is described as insensitive to reward or punishment-based feedback has been rejected. In fact, contrary to this hypothesis, previous research (Galea et al 2015) has demonstrated a double dissociation, with the two types of feedback, positive or negative, having independent effects on the learning and retention components of motor learning tasks.

The findings revealed that negative feedback accelerated learning, whereas positive feedback did not, but had an impact on increasing motor memory retention when performance feedback was removed. These previous findings call into question the assumption that motor learning is independent of motivational feedback, and they raise new questions regarding the neural basis of negative and positive motivational feedback in motor learning. It is well known that reward and punishment are impactful modulators of human and animal behaviour (Thorndike, 1911; Pavlov, 1927; Skinner, 1938; Sutton and Barto, 1998). However, there is a scarcity of information on how reward and punishment influence the learning of specific behaviours.

Previous research (Galea et al., 2015) project investigated the effects of reward and punishment on procedural learning, which required continuous modulation of motor output and differentiated

reinforcement and nonreinforcement learning. It was agreed to use monetary rewards because they are a powerful modulator of human behaviour and have clear effects on brain activity (Breiter et al., 2001; Delgado et al., 2003). Both manipulations, rewarding the desired behaviour and punishing the undesired behaviour had a measurable effect on future actions. However, the fact that the effects on the behavioural measures were qualitatively distinct suggested that reward and punishment may engage qualitatively different motivational systems. If reward and punishment access different motivation systems, one would expect this to be reflected in the neural substrate. In a previous study, dorsal and ventral striatal activity related to reward per se replicated previous findings (McClure et al., 2003; O'Doherty et al., 2003, 2004) and most likely represents the neural correlate of dopaminergic neurons coding a prediction error signal, in addition to being consistent with the two-process account of reinforcement learning (Montague et al., 1996; Sutton and Barto, 1998). Punishment, on the other hand, resulted in activation predominantly in the inferior frontal gyrus and the insula, the latter being the most consistently activated area in a variety of punishment-related studies (Elliott et al., 2000; Sanfey et al., 2003; Daw et al., 2006). Punishment, even when associated with striatal activation (Seymour et al., 2004), is thought to be mediated by the serotonergic system originating in the median raphe nucleus rather than the dopaminergic system (Ungless et al., 2004, Daw et al., 2002). In our case, activating such a motivational system resulted in a change in performance, with which the insula was the only area that was significantly correlated. Thanks to this previous study, it was possible to correlate the neural substrates of reward and punishment with qualitatively different behaviour outcomes, implying that these modulators may indeed operate through use of different motivational systems. Seeking reward and avoiding punishment are powerful motivating factors that shape human behaviour, and the ability to change behaviour to achieve desired outcomes is essential. The ability of the motor system to adapt to changes in the environment is critical for performing accurate movements (Tseng et al. 2007). Understanding the processes of this ability is therefore required in order to understand the underlying mechanisms of motor learning and decision making.

Motor adaptation refers to a particular type of behavioural change that involves adjusting how an already well-practiced action is performed in order to maintain performance in response to a change in the environment or the body, either by selecting an alternative well-practiced action or modifying how the current action is executed. In either case, the action's goal (e.g., reaching a target) remains the same. Because both our bodies and the environment with which we interact change, adaptation is critical to our ability to perform accurate movements. One important aspect of adaptation is that it allows individuals to change their motor commands in response to errors in previous movements. The need to maintain our skills updated in an ever-changing environment appears to be so prevalent

that the motor system is likely to be equipped with a dedicated mechanism for recalibrating our actions. The cerebellum is extremely important in this mechanism. Many different tasks have shown adaptation (Krakauer et al. 2000; Martin et al. 1996; Morton and Bastian 2004; Reisman et al. 2005; Shadmehr and Mussa-Ivaldi 1994) and the cerebellum appears to be required for this type of learning (Chen et al. 2006; Diedrichsen et al. 2005; Martin et al. 1996; Maschke et al. 2004; Morton and Bastian 2006; Smith and Shadmehr 2005).

Indeed, neuropsychological research has suggested that successful error reduction during adaptation is a cerebellar-dependent process. The cerebellum has been demonstrated to be an important area with a significant role in prediction. According to research, the brain is constantly making predictions about future events. Theories of prediction on motor learning propose that the brain reduces the discrepancy between expectation and actual experience, i.e., the prediction error. In a previous work, cerebellum has been demonstrated as an important part of the neural network involved in goal-directed movement adaptation. (Ito 1972, 1982; Martin et al. 1996; Mazzoni and Krakauer 2006; Wallman and Fuchs 1998; Wolpert et al. 1998).

One of the previous study's assumptions involves error-based learning as a process that is strongly influenced by both the punishment and reward processes, and as predicted, it has been revealed that the reward, as positive feedback, causes increased memory retention while the punishment leads to faster learning.

To the purpose of this research, we are interested in reinforcement learning, which involves updating motor performance using reinforcement signals. The brain must infer the outcome of such signals (success or failure), and this mechanism has led people to learn from it and produce motor performance in order to achieve their goals.

Although it is true that reinforcement learning in human motor tasks has received little attention, recent evidence suggests that reaching movements can be altered through explicit reward. Reinforcement learning seeks to maximize future rewards. Dopaminergic neurotransmitters from the ventral tegmental area to the primary motor cortex may be a neural correlate of reward signals. Reinforcement learning is an adaptive process in which an animal utilizes its previous experiences to improve the outcomes of future choices. Value functions, which describe how much future reward is expected from each action, are used to select actions. Reward and punishment can be used to modify value functions. Individuals are taught a reward and punishment system in which they are rewarded for correct moves and punished for incorrect ones. Individuals try to minimize wrong moves while maximizing right ones in this manner. Reinforcement-learning (RL) focuses on learning from unexpected events or prediction errors (Schiffer et al., 2017).

The aim of our research is to investigate if this effect exists in expert musicians, such as pianists.

13

Therefore, in case, we would additionally like to examine how having a higher level of anxiety influences the adaptation of our behaviour to positives or negatives feedbacks, and how our behaviour is influenced by that.

2.2 Decision Making

Decision making is a crucial process and is the underlying mechanism which makes possible the reinforcement learning process. As a result, it is meaningful to evaluate. The ability of humans and other animals to choose between competing courses of action based on the relative value of their consequences is referred to as decision making process. This capacity is therefore fundamentally integrative combining the complex cognitive processes that encode, retrieve, and maintain relationships between actions and consequences in working memory with the motivational processes that determine the value, or utility, of actions or sequences of actions. Much of the recent success in decision making research originated from the recognition that the interaction of cognitive, motivational, and behavioural processes engaged during the course of specific decisions cannot be reified to a single specialized circuit, cell type or intracellular process and is best understood at a systems level.

Lee et al. (2007) review research on the involvement of the prefrontal cortex in decision making in primates and propose that the lateral, medial, and ventral subregions may have the more specialized task of deriving predictions about the future value of reward based on states, actions, and local predictive cues, respectively, in light of the connectivity of subdivisions of this region and formal theories of decision making. Interestingly, Murray et al. (2007), based on a review of the comparative literature, reached similar conclusions about the role of OFC in decision making. They emphasized the role of OFC in deriving reward value from predictive cues, as well as to evidence that suggested that OFC may play a specialized role by allowing animals to compare values across distinct event categories.

The decision-making process that begins with representing the available options and ends with selecting the option with the highest expected value is one of the two core components of goal-directed behaviour. The second component is reinforcement learning (RL), which uses outcomes to improve decision-making by refining value expectations.

Human decision-making is likely to be exposed to biases (i.e., differences from normative prescriptions), such as the framing effect. While the investigation of decision-making biases has a long history in economics and psychology, learning biases have received far less attention. This is surprising because most decisions we make in everyday life are based on experience, and choice contexts are recurring, allowing learning to occur and therefore also influencing future decision-making. It has been discovered that affective state and decision making are inextricably linked

(Lerner et al., 2015). Anxiety, in particular, has been shown to cause insufficient adaptation to environmental change (Browning et al., 2015; Huang et al., 2017), disruption in learning, and maladaptive biases in both aversive and reward-based learning contexts (Hein et al., 2021; Huang et al., 2017; Kim et al., 2020; Lamba et al., 2020; Piray et al., 2019; Pulcu and Browning, 2019). Anxiety symptoms have a strong influence on decision making. Indeed, in decision making task anxious participants learn more from negative feedback (Bishop et al., 2018).

Chapter 3: Anxiety's impact on neural activity and music performance

3.1 Anxiety

Overall, data suggest that anxious people are quicker to update and change their behaviour in response to negative outcomes.

Anxious individuals performed better, showing increased accuracy, after negative compared to positive feedback. Negative avoidance is observed in anxious individuals. That is, anxious people put considerable effort trying to avoid negative feedback and are thus more likely to learn faster from negative than positive feedback (Taka´cs et al., 2015). As a result, the researchers predicted that anxious people would have a higher negative bias and thus perform better after negative feedback than after positive feedback. Negative feedback bias, as previously stated, is defined as performing better after receiving negative feedback than after receiving positive feedback. This bias would be reflected in a positive relationship between anxiety measures and increased task performance after receiving negative feedback but not after receiving positive feedback. According to recent findings (Bishop, 2008; Taka´cs, et al., 2015) anxious individuals appear to expect negative feedback more readily, resulting in a lower feedback-related negativity component (FRN). A positive correlation between anxiety levels and the event-related potential (ERP) response to negative feedback should capture this.

According to the differences in FRN amplitude, anxious individuals perceive less of a difference between expected and received negative feedback (Hauser et al., 2014; Ichikawa et al., 2010). As a side effect, anxious individuals appear to expect negative rather than positive feedback and are less surprised when they receive negative feedback. This could be interpreted as anxious people having a negative bias when learning through reinforcement. This negative bias seems to decrease subjective conflict between expected negative feedback and actual negative feedback received. The fact that anxious people expect more negative feedback and, as an outcome, perceive less conflict than those who receive positive feedback may facilitate in their learning after receiving negative feedback. Finally, even at subclinical levels, anxiety symptoms lead people to expect more negative feedback (Jones et al., 2021).

Anxiety has been shown in both anxious and non-anxious people to impair cognitive functioning and modify preferences for feedback-based learning (Jones et al., 2021). Anxiety is the most common mental health issue afflicting people worldwide (Mkrtchian et al., 2017). Increased anxiety, defined as a negative multidimensional state (Gibson, 2014), is known to cause debilitating physiological changes in the sympathetic nervous system. Furthermore, anxiety significantly impairs cognitive functioning, including the ability to regulate emotion (Endler & Kocovski, 2001; Gu et al., 2010a; Xu et al., 2013), create positive expectations (Mitte, 2007; Shepperd et al., 2005; Wray & Stone, 2005), and adapt decision-making, particularly when outcomes are uncertain (Poorman et al., 2019; Eysenck et al., 2007). In uncertain environments, increased anxiety and stress significantly raise the use of attentional resources directly aimed toward potential threats (Bishop, 2008). Individuals exhibit vigilant-avoidant behaviours in such situations, especially as their ability to think objectively begins to deteriorate. This is just one example of the complicated interactions that exist between anxiety and decision-making.

Anxiety is characterized by altered responses in the face of uncertainty, but the precise mechanism by which uncertainty alters anxious people's behaviour is unknown (Aylward et al., 2019). Despite the fact that anxiety disorders are among the most common mental health problems in the developed world, we still have limited understanding of the mechanisms underlying pathological anxiety and the associated changes in cognitive processes, such as decision-making, when people are anxious. Anxiety is thought to manifest as a direct consequence of altered psychological, behavioural, and neural responses to uncertainty. Anxious people report finding uncertain situations extremely distressing, so they will tend to avoid uncertain decisions, preferring more predictable options over more profitable but extremely uncertain options (Aylward et al., 2019).

Decisions are made based on the relative value determined to reward and punishments, which alludes to how much one individual anticipates liking being rewarded or disliking being punished, as well as how quickly the information is integrated over time. The learning rate reflects how quickly a person switches between options after receiving a punishment or how long a person persists in selecting a previously rewarded choice. Individuals with high levels of anxiety symptomatology should experience a different impact from the reinforcement learning framework. Specifically, given that anxiety is associated with a bias towards aversive processing feedback, which means that people who suffer from anxiety tend to focus their attention primarily on negative feedback, the prediction would be that anxiety selectively increases the weights of aversive-specific feedback in reinforcement learning.

The discovery that anxiety symptoms are associated with altered decision-making in the aversive domain leads to the conclusion that anxious people have a higher rate of punishment learning. A

greater punishment learning rate means that individuals with anxiety symptoms learn faster during a punishment condition (negative feedback), and as a consequence, they will more rapidly update their behaviour based on negative outcomes. Clinically, this could lead to an overestimation of negative events. For example, in the aftermath of a widely publicized plane crash, an anxious individual may overestimate the likelihood of a recurrence and thus avoid flying. With anxiety symptoms, it may be critical to focus on treatment that can mitigate such a negative bias. We should concentrate on treatments that aim to change how negative information is processed. Indeed, changing how people use the same information is one of the underlying principles of psychological interventions for mood and anxiety disorders, such as cognitive behavioural therapy.

Anxiety is characterized by physiological and psychological changes in responses to an unknown future threat (Grupe and Nitschke, 2013; Bishop, 2007). Individuals with high trait anxiety, according to research, do not correctly estimate the likelihood of outcomes during aversive or reward learning in uncertain environments (Browning et al., 2015; Huang et al., 2017; Pulcu and Browning, 2019). These findings move researchers closer to formalizing the behavioural effect in a reinforcement learning model, as well as directly measuring it and thus refining future treatments. Furthermore, it has been demonstrated in a reinforcement learning framework, that the exploration phase, in which the individual first engages in the motor task, is impaired in anxious individuals (Sporn et al., 2020). Indeed, during the exploration phase, movement variability is critical, and anxiety symptoms appear to have a strong impact on this motor learning's component. Movement variability is increasingly recognized to benefit motor learning as a form of action exploration (Todorov and Jordan, 2002; Wu et al., 2014; Pekny et al., 2015), particularly during reward-based learning, with disparate effects in motor adaptation paradigms (He et al., 2016; Singh et al., 2016). In fact, an anxious state leads to ritualistic behaviour, which is characterized by movement repetition and rigidity (Lang et al., 2015). As a result, anxiety reduces motor learning variability, which impairs motor learning. This impairment is exacerbated in situations with the uncertain outcomes, such as a reinforcement learning process, in which the individual will not receive additional feedback on the types of errors that may occur.

Another component that anxiety may influence is the ability to adapt to changes during the motor learning task. It has been discovered how anxiety, specifically in the context of rewarded-based motor learning, affects an individual's ability to estimate the environmental uncertainty about the stability of the task structure, both in aversive and rewarded-based tasks (Browning et al., 2015; Huang et al., 2017; Pulcu and Browning, 2019). This means that individuals who suffer from anxiety and are engaged in a reinforcement learning task will find it difficult to adapt their behaviour as the task structure changes during the learning process. For example, anxious people

17

will be unable to change their movements based on the scores they receive every time they stop playing. That is because they are too focused on the environmental uncertainty rather than being able to elaborate the feedback they received and, consequently, they will not be able to adapt their behaviour based to improve their motor learning.

Finally, anxiety has a significant impact on the neural level. In fact, behavioural variability reflects variability in premotor and motor cortex neuron activity during motor movement planning (Churchland et al., 2006). Sensorimotor beta oscillations have been discovered to be brain rhythms associated with the modulation of motor exploration and variability.

As a result, anxiety symptoms appear to have a significant influence on decision-making tasks. Anxiety can also affect how a person performs a task, making it difficult to learn a new manual skill, such as playing the piano. Anxiety can, in fact, influence movement. Increased movement variability is known to benefit motor learning (Todorov and Jordan, 2002; Wu et al., 2014; Pekny et al., 2015), and this aspect is impaired when people are anxious. There is also evidence that anxious individuals learn less from the consequence of their actions. As a result, anxiety symptoms appear to cause individuals to be less flexible when adapting movements during a motor task.

3.2 Beta oscillations

Sporn and colleagues conducted an experiment in which people learned to play a short sequence of notes on a piano in order to better understand how anxiety may affect motor task learning. The main experiment included 60 people and was divided into two phases. Participants in the first "exploration" phase were required to play the piano sequence at their own pace, using any timing they desired, and encouraged to experiment with different rhythms. During the second phase, participants were awarded higher scores for getting closer to a specific rhythm.

The subjects were split into three group. During the exploration phase, one group was subjected to an anxious task, such as public speaking. A second group was only told about the anxiety-inducing public speaking during the learning phase, while the other was a control group that was not exposed to any anxious trigger.

The results showed that there was no difference between the control and the second groups, but regarding the first group, which was exposed to anxious feelings during the exploration phase, was found to be less likely to learn the piano sequence and to explore less, producing different movements compare to the other two groups. Sporn et al. used electroencephalography, a technique for recording brain activity, to compare participants with and without anxiety (EEG). Anxiety altered rhythmic patterns of brain activity known as "sensorimotor beta oscillations," which are known to be involved in both movement and learning, according to EEG signals.

Brain waves are a method of measuring brain communication. Beta oscillations are brain waves that

occur between the frequencies of 13Hz and 30Hz (Barone & Rossiter, 2021; Espenhahn et al., 2019). Beta oscillations have been linked to sensory-motor processing, motor learning, and reward processing (Barone & Rossiter, 2021; Engel & Fries, 2010). Low-power beta oscillations (13Hz to 20Hz) and high-power beta oscillations (20Hz to 30Hz) have significant differences (Barone & Rossiter, 2021).

Brain rhythms, also known as oscillations, are associated to a wide range of cognitive functions, and can be classified into several oscillatory bands (Buzsáki, 2006). Sensorimotor processing is frequently associated with beta oscillations (13-30 Hz) (Pfurtscheller and Lopes da Silva, 1999; Baker, 2007). Beta oscillations are considered as short bursts of temporally localized activity (Feingold et al., 2015; Sherman et al., 2016; Shin et al., 2017; Tinkhauser et al., 2017; Torrecillos et al., 2018; Little et al., 2019). These oscillations occur during stable postures and decrease during active states, such as movement planning and execution (Engel and Fries, 2010; Kilavik et al., 2013). Sensorimotor cortex (Jensen et al., 2005; Roopun et al., 2006; Kramer et al., 2008; Yamawaki et al., 2008; Kopell et al., 2011) and basal ganglia are the two primary sources of beta (Holgado et al., 2010; McCarthy et al., 2011; Tachibana et al., 2011; Mirzaei et al., 2017).

Beta oscillations reflect brain rhythm and are modulated by various aspects of performance and motor learning (Herrojo Ruiz et al., 2014; Bartolo and Merchant, 2015; Tan et al., 2014), as well as in reward-based learning (HajiHosseini et al., 2012). Changes in sensorimotor beta oscillations have been found to mediate the effect of anxiety on belief updates and the estimation of uncertainty driving reward-based motor learning. During the initial exploration phase, anxiety was used to reduce task-related motor variability. When the dynamic changes in neural activity of beta oscillations were investigated, it was discovered that this reduction was associated with altered dynamic in beta-band oscillatory activity.

Beta power has been linked to slower feedback learning: participants who have more beta power during feedback processing learn slower. Thus, it has been established that anxiety during the initial exploration phase reduced motor variability, and anxiety during the initial exploration phase was associated with elevated sensorimotor beta power and a longer beta power burst. These findings provided the first evidence that anxiety alters the distribution of sensorimotor and prefrontal beta bursts, as well as beta power, which may account for observed deficits in prediction update during reward-based learning. Furthermore, higher sensorimotor beta power at the end of the sequence performance was related to a more restricted use of task-related variability (Churchland et al., 2006; Mandelblat-Cerf et al., 2009; Santos et al., 2015).

Previous research (Sporn et al., 2020) has shown that low-power beta oscillations are involved in feedback-based action updating (Yaple et al.,2018; Galea et al., 2015). Sporn et al. (2020)

discovered that people with state anxiety disrupt this process, as high-power beta oscillations reduced learning rate in a motor learning task. Thus, if it is true that people in general learn faster with negative feedback, and this aspect is accentuated if people suffer from anxiety symptoms, we can expect an accelerated learning rate to be associated with decreased beta power under a negative feedback condition. Indeed, this prediction is the second hypothesis we established in our study; we are interested in determining whether the participant has lower beta power when processing negative feedback than when processing positive feedback. Pollok et al. (2014) discovered that when using feedback, the amount of beta power suppression is correlated with the improvement of reaction times in a motor learning task. The lower the beta power in their study, the faster the participants' reaction times improved (Pollok et al., 2014). This finding backed up the theory that lower beta power is associated with faster learning and that beta power modulation is a biomarker of functional reorganisation in motor learning associated with adapting pre-learnt sequences, such as playing the piano. This means that the amount of beta power present during motor learning is a good indicator of how well previously learned sequences were adapted (Pollok et al., 2014). Sporn et al. (2020) discovered that individuals with state anxiety, as explained below, had high beta power bursts after receiving feedback. These bursts were associated with slower reward-based motor learning, as indicated by a lower score on a motor task, whereas higher scores indicated a faster learning rate. Participants in this study who were not anxious showed consistent low-level beta power, which was associated with accelerated motor learning.

3.3 Music performance anxiety in skilled pianist

Regular practice is essential when learning how to play an instrument because it reduces errors and stiffness in performance through increased familiarity (Watson, 2006). Learning how to play an instrument necessarily requires motor learning. Feedback allows individuals to adapt their motor performance during the motor learning process (Watson, 2006; Cech & Martin, 2012). That is, feedback is an essential component of learning and development in every field of human achievement. We rely on feedback, which can range from self-observation of our own efforts to master a new concept or skill to comments and suggestions from our teacher, coaches, and supervisors, all of whom help us monitor and improve our performance, build our confidence, and cope with even the most mundane learning situation.

As a direct result, it is surprising that there is so little understanding of the concept in music beyond describing the process of providing information back to a learner in order for that person master some sort of musical skill.

Music performance anxiety (MPA) is categorized as a form of social anxiety. According to the DSM-5, social anxiety is defined as a strong fear of one or more social situations in which the

individual may be scrutinized by others. Examples include social interactions (e.g., having a conversation), being observed (e.g., eating or drinking), and performing in front of others are all examples (e.g., giving a speech) (American Psychiatric Association, 2013, a, p. 202). Music performance anxiety occurs when anxiety appears during a musical performance (MPA; Kenny, 2010; Kenny & Osborne, 2006). The professional lives of musicians can be hampered by performance anxiety. According to Kenny, MPA is "the experience of marked and persistent anxious apprehension related to musical performance [...] manifested through a combination of affective, cognitive, somatic, and behavioural symptoms" (2010, p. 433). MPA research has grown in the last few decades (e.g., Kenny & Osborne, 2006; Osborne & Kenny, 2008; Studer et al., 2011). According to Kenny (2016), rumination is a cognitive of the vicious cycle of anxiety. However, in the field of MPA, rumination has yet to be thoroughly researched. It has been classified as post-event rumination in the context of MPA among music students (PER). PER is defined as the process of thinking and rethinking about a recent social interaction, including sel-appraisal and other event-related elements (Kashdan & Roberts, 2007). After-event rumination has been identified as a key feature of social anxiety disorder (Abbott & Rapee, 2004; Kocovski, Endler, Rector, & Flett, 2005; NolenHoeksema, Wisco, & Lyubomirsky, 2008). Over two days following a soloist concert, it examined the development of negative and positive rumination in performing musicians. The research hypotheses were that increasing MPA levels would be associated with more negative and less positive PER, and that as MPA levels increased, negative PER would decrease more slowly, and positive PER would increase faster. Previous research (Nielsen, C., et al., 2018) found that negative PER increased with increasing usual MPA level, and that high-anxious music students had more negative and less positive rumination after a 10-minute solo performance than low-anxious music students. These findings support the Clark and Wells (1995) and Rapee and Heimberg (1997) models of social anxiety, which claim that people who are socially anxious ruminate more negatively after a stressful social event than people who are not anxious. As expected, the pattern of development for negative PER was dependent on the usual MPA level. Many professional musicians are affected by music performance anxiety (MPA), and anxiety in general has been identified as a factor that increases attention to negative feedback (Kenny, 2005; Gelenberg, 2000). Even non-anxious professional musicians have been observed to exhibit stress symptoms such as elevated heart rate prior to a performance, which could be related to increased attention to negative feedback in performance settings (Kenny, 2004). Music performance anxiety (MPA) affects 50% of professional musicians, a condition in which musicians experience cognitive and physiological symptoms such as trembling hands and fear when performing music (Fernholz, Mumm, Plag, et al., 2019). While the phenomenon itself describes

musicians experiencing anxiety before or during a performance, no conclusive theoretical framework for defining and categorizing MPA has been developed (Kenny 2004a). Many researchers classify MPA as a social phobia (Sieger, 2017). Some researchers disagree, but the fear of being evaluated by an audience is shared by MPA and social phobia (Sieger, 2017). Individuals with social phobia perceive the majority of people they encounter as audience members, whereas MPA musicians experience people listening to their musical performance as audience members (Osborne & Franklin, 2002). The main similarity between social phobia and MPA is the fear of negative feedback regarding a social or musical performance (Osborne & Franklin, 2002). When it comes to musical performance, musicians with MPA have a negative learning bias and perceive negative feedback as a threat (Guyon, Studer, Hildebrandt, & al., 2020). According to Guyon et al., these situations are perceived as threatening when an audience's perceived demands exceed the perceived resources available (Guyon et al., 2020). This means that musicians would feel threatened if the perceived standard of such an audience was higher than their perceived abilities. One reason why musicians with MPA are more likely to adapt negative feedback is because of the potential consequences. Social consequences, such as a bad reputation, as well as internal consequences, such as a sense of failure, could be among them. Uncertainty about employment, a demanding environment, and the competitive nature of music performance are all social stressors that enable MPA and can be accelerated by negative feedback (Fernholz et al., 2019).

Despite the fact that many musicians regard music performance anxiety (MPA) as a critical matter, research into the psychobiological and performance-related aspects of MPA is limited. MPA is defined as "the experience of marked and persistent anxious apprehension related to musical performance (...), manifested through combinations of affective, cognitive, somatic, and behavioural symptoms." According to the literature, state anxiety is higher before and during a public performance (i.e., in front of an audience or jury) than it is during a private performance (i.e., without an audience or jury). Many studies have shown that people who have a cardiovascular challenge pattern before cognitive and motor tasks perform better than people who have a cardiovascular threat pattern. Using cardiovascular measures rather than self-reports to assess challenge and threat has advantages because it does not rely on individuals' ability or willingness to accurately report on their experiences, especially when nonconscious and irrational influences are at work. Furthermore, in terms of predicting performance, cardiovascular challenge-threat indices outperform self-reported variables. Anxious pianists reported lower expectations of completing several piano performance tasks than non-anxious pianists, implying that increasing levels of MPA may be associated with greater threat/lesser challenge.

MPA has also been linked to reactions to loss of control, fear of negative evaluation and judgmental

attitudes (Lehrer, 1987), social situations, crowd phobia, and catastrophizing (Steptoe & Fidler, 1987).

It has been established that music performance anxiety (MPA) is a serious problem for many musicians because performance impairment caused by MPA can negatively affect their career. All of these findings have shown how anxiety state can impair with musicians' performance. As a result, it is becoming a real issue that should be investigated through scientific research.

Chapter 4: The research

4.1 Introduction

The goal of this research is to determine whether pianists learn faster from negative feedback than from positive feedback in a music performance-related motor learning task. This study will also investigate whether the negative learning bias in trait MPA is accompanied by a decrease in cortical beta oscillations. Thus, we hypothesize that pianists will learn faster from negative feedback than from positive feedback, and that this faster learning rate will be mediated by reduced beta oscillations in sensorimotor and prefrontal areas.

As a result, this study approached various topics, such as feedback elaboration, motor learning process, anxiety symptoms and beta oscillations.

The primary function of feedback is to allow individuals to adjust their future actions based on new information. Typically, new information corresponds to the consequences of the recently produced action. This process of adapting future action is determined by the individual's desired outcome. If the outcome is positive feedback, such as a reward, the individual is more likely to continue with that specific action.

Previous research (Galea et al. 2015) has shown that positive and negative feedback are processed and adapted differently; this is especially important because it is related to one of our project hypotheses. Indeed, it has been demonstrated that positive and negative feedback have distinct effects on the learning process. There is evidence, for example, which shown that people tend to learn faster from negative feedback due to a learning bias. Furthermore, other research has discovered that people who suffer from anxiety symptoms tend to focus more on negative feedback than positive, and thus learn faster from them (MacLeod & Mathews, 2012).

Furthermore, previous research (Fernholz et al. 2019) has found that musician's population tends to suffer from anxiety symptoms and anxiety symptoms have a strong influence on how individuals process different types of feedback (Kenny, 2005; Galenberg, 2000).

Additionally, it has been revealed that individuals experiencing anxiety symptoms have an increased power in beta oscillations. Beta oscillations can be described as a frequency band in

23

neural activity. Beta power had been shown to be closely associated to learning, specifically reduced learning from feedback: individuals with higher beta power during feedback processing learn more slowly from feedback (Sporn et al. 2020). Indeed, changes in beta oscillations have been linked to bias in feedback processing (Sporn et al. 2020; Galea et al. 2015; Yaple et al. 2018; HajiHosseini et al. 2020), and Sporn et al. (2020) established a direct interaction between beta oscillations, motor learning from reward feedback and anxiety.

Previous research on motor learning (Krakauer et al. 2019), feedback (Galea et al. 2015), beta oscillations (Sporn et al. 2020), and anxiety symptoms in humans (Jones, D. L., et al. 2021), particularly musicians, lends support to these hypotheses. We expect pianists to rely on negative feedback to change their future behaviour while participating in a motor learning experiment. As a result, if they are processing negative feedback, we anticipate that they will adapt their actions more quickly. Furthermore, we anticipate that this result will be accompanied by a decrease in cortical beta oscillations.

Our research is based on a motor-learning paradigm to assess learning rates, in which participants had to find the unknown dynamic in two different melodies while receiving positive and negative feedback in two independent trial runs.

4.2 Methods

4.2.1 Participants

In this study the sample consisted of 25 pianists (14 F, 11 M) with a mean age of 29.4 (age range 18-65 years). The study was submitted to the University of Goldsmiths Ethics Committee for approval, which evaluated the research and granted ethical approval. Before the study began, all participants signed an informed consent form outlining the study's purpose, procedures, risks and benefits, and participation options. Participants were able to ask questions and make an informed decision about their participation. Before beginning the study, participants signed an informed consent form.

The recruitment phase was made via flyers across the University and via social media as well, like for instance Facebook.

To take part to the experiments, there were specific inclusion and exclusion criteria. All the participants must have been pianist with at least 6 years of musical training. They have possessed normal or corrected vision; normal sense of hearing and they must have been over 18 years old and under 65 years old. Regarding the exclusion criteria, this study has not been conducted with individuals clinically diagnosed with a neurological or psychiatric or neurodevelopmental conditions or individuals suffering from cardiovascular disease. Neither can individuals participate

in this study in case they had been currently taking medication to treat depression or anxiety conditions. Furthermore, the day before the experiment, all the participants have been informed to avoid wearing a dress or a full body jumpsuit because that should have complicated the electrodes application' process.

All the participants have been compensated a base rate of 35 GBP and depending on their performance they could have earned up to an additional 5 GBP.

Unfortunately, due to technological issues in the lab, such as equipment's malfunction, in this case the recording devices had problems which led to data loss or inaccurate data. That is why EEG data could only be evaluated for 10 participants rather than 25. However, the experiment is still ongoing, aiming to recruit additional pianists.

Participants were instructed to read the information sheet and sign the consent form prior to the experiment. However, the participants had the possibility to withdraw the experiment at any time. They had to fill out the general demographics form, which includes their date of birth, gender, and the number of hours they had played piano in their lifetime. They were then asked to complete the Music Performance Anxiety Inventory-Revised (K-MPAI-R) (Kenny, 2009). Usually, the participants were instructed to fill out this questionnaire just before showing up to at the lab. However, some of the participants accomplished it as soon as they completed the consent form, read the information sheet and filled out the general demographics form.

4.2.2 Anxiety Assessment

Kenny and colleagues created a 26-item questionnaire in 2004 called the Kenny Music Performance Anxiety Inventory (K-MPAI), which was later revised and expanded into a 40-item version called the Kenny Music Performance Anxiety Inventory-Revised (K-MPAI-R) (Kenny, 2009). This study utilized the Kenny Music Performance Anxiety Inventory-Revised (K-MPAI-R) questionnaire to assess anxiety level. The revised version of the K-MPAI (Kenny, 2009) consists of 40 items, which are also presented as a 7-point Likert scale ranging from 0 (strongly disagree) to 6 (strongly agree), or inversely, depending on the statement regarding anxiety-related discomfort during musical performances.

Anxiety, according to Kenny, is the result of the interaction of three factors (i.e., vulnerabilities): (a) a generalized biological (heritable) vulnerability; (b) a generalized psychological vulnerability created by prior experiences in developing a sense of control over significant situations; and (c) a more specific psychological vulnerability in which anxiety is associated with specific environmental factors. According to the Kenny questionnaire, the systems involved in anxiety are the somatic response (the "flight or fight reaction, which prepares the body for escaping or fighting"); the emotional and cognitive response (worry, dread, lack of concentration, memory

loss); and the behavioural manifestations (technical errors, memory loss, performance breaks, avoidance of performance opportunities).

A high total score indicates a high level of performance anxiety and distress. The original version of the K-MPAI as well as the revisited version have the same internal consistency (α = .94; Kenny, 2009), suggesting that the items on the scale are highly interrelated and measure the same underlying construct. This indicates that the scale is likely a reliable and valid measure of the concept being measured. K-MPAI-R is based on Barlow's model of anxiety, which is a theoretical framework that explains the development and maintenance of anxiety disorders. The model is based on the premise that anxiety disorders are caused by a combination of biological, psychological, and environmental factors. According to Barlow's model, anxiety disorders are the result of a complex interaction between biological vulnerabilities, such as genetic predispositions and physiological reactions to stress, and psychological factors, such as negative thinking patterns, cognitive biases, and learning experiences.

4.2.3 Procedure

As soon as the participants had finished the forms and filled out the questionnaire, they were introduced to the MIDI piano. They had been given two melodies and they were asked to play those two melodies briefly. Participants were presented with two 16-note melodies (Figure 3), which they had to play with the according fingers as noted in the melodies. The number specified above the notes corresponds to specific fingers, which are thumb (number 1), index (number 2), middle finger (number 3) and ring finger (number 4).

Melody 1

Melody 2

Figure 4.2 Representations of the two melodies (Figure 3)

In the beginning, the participants had 5 minutes to familiarize themselves with the melodies, which means they could play on their own time. Once 5 minutes had passed, they had to practice both melodies at the right tempo, which was 120bpm, using the metronome. The metronome could not be engaged during the experiment, but the participants were encouraged to practice using it. They all had been informed that to participate in the study they will need to remember both two melodies. We also asked them to play without looking at their hands, since during the experiment they will need to look at the screen in front of them. After having been sure they could play the melodies five times consecutively without mistakes, we asked them to stop playing. While the participant was practicing with the melodies, we had been preparing the technical setup on the table.

Once the participants had finished practicing the melodies, we asked them to sit in front of the table where we disposed of all the technical instrumentation. We consequently proceed to place the EEG cap on the skull and add the external electrodes to measure both the electrocardiogram (ECG) and the electrooculogram (EOG). At this point, the participants were ready to start the experiment.

4.2.4 Experimental Task

We were asked to stare at a fixation point for 5 minutes while we were recording the resting state (baseline). In this phase, the participants were instructed to try to stay as relaxed as possible and

27

look at a black cross on a white background placed on the screen. After the baseline was recorded, the real experiment could start.

Participants performed on a digital piano. The experiment task was divided into two trials of two different feedback conditions. For each feedback block, positive and negative condition, the participant had 100 trials. That means that the participant was instructed to play one of the two melodies, for example, melody 1, for 50 trials and then melody 2 for the other 50 trials with one of the two feedback conditions, for example with positive feedback. We then asked them to repeat the 100 trials, separated into 50 trials, with the negative condition block, playing 50 times melody 1 and other 50 times melody 2. The sequence for commencing either positive or negative feedback as the first task was determined at random by the computer. Depending on whether the participant started with the negative or positive feedback condition they received the instructions applicable to their feedback condition. The instructions for the experiment were explained for both the positive block and the negative block. For instance, regarding the positive feedback block, the participants were instructed to play one of the two melodies 50 times and their goal consisted in finding the hidden rhythm dynamic each time. Participants were made aware that the target dynamic exists. The targeted dynamic was created within the range of the default linear velocity mapping (range of keystroke velocity 0–127).

They had to play two different 16th-note melodies in two separate blocks. They were told that the fist 8 notes and the last 8 notes (repeated pattern) have the same dynamic and that they will receive a score from 0 to 100 (in the case of positive feedback block, while for the negative feedback block the score would have been from -100 to 0) each time. They were also warned that the solution may not be the one that could make more sense based on their musical training. After 50 trials of either a positive or negative feedback block participants were offered a short break and then proceeded with the last 50 trials of the current feedback block.

After the instructions were clear, a practice run consisting of 5 trials was used to explain the navigation of the task. The trials were initiated by pressing a pre-defined key on the piano with the left index finger when the visual cue (Figure 4) was given. Feedback and visual cue were provided on the screen placed in front of the participant. Positive feedbacks were displayed in a number from 0 to 100, where increased closeness to 100 indicated closeness to the target dynamic. Negative feedback was presented in a number from 0 to -100 where closeness to 0 indicated closeness to the target dynamic. Pitch errors were displayed as an achieved score of 0 in the positive and -100 in the negative feedback condition. The participants did not receive any further feedback regarding their performance.
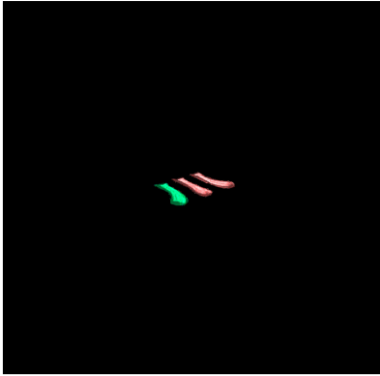
Figure 4.2 Visual cue to start a trial (Figure 4)

When the first trial block was started the EEG recording started saving. This range of feedback scores is typically used in the motor control literature (Galea et al. 2015). The feedback score was presented on the screen at the end of the trial, seven seconds after a go signal. The feedback remained on the screen for 1.5 seconds.

As soon as the 100 trials of one feedback block were finished, the participants received the instructions for the next feedback block, which was different to the one they had already finished because they had to aim to the oppositive score. In other words, during positive feedback block they needed to try to reach a score close to 100 while in the negative feedback block, they needed to reach 0, which was the best score in this condition. The procedure here repeated itself from the first feedback block. Participants were given a debrief form and instructions as to how they would receive their payment.

As a result, the participants were instructed to repeatedly play a music melody and infer the rewarded hidden target: a specific dynamic pattern. Participants used trial-based feedback to update their beliefs on the hidden target and improve the overall feedback score. There was no prior information available to the participants regarding the dynamic pattern.

4.2.5 Experiment design and Behavioural Analysis

This study employed a within subject's design. That means that each participant is exposed to different conditions, in our case positive feedback vs negative feedback, which allows researchers to compare the effects of different factor within the same person. A within-subjects design is a research method that involves studying the same group pf participants under different conditions or treatments. In this type of design, each participant serves as their own control group, meaning they receive all of the treatments or conditions being studied. One advantage of within-subjects design is that it reduces the variability between participants, which can increase the accuracy of the results.

To assess behavioural data, we used R studio's software with a linear mixed model. R studio is a software for statistical computing and data analysis.

The accumulated behavioural data was analysed with a two-way RM-ANOVA to assess if the type of feedback received, positive vs negative, increased the scores indicating closeness to the hidden dynamic, but also the rate at which the scores increased.

4.2.6 EEG Recording and Pre-Processing

EEG data was pre-processed by a code written by Maria Herrojo-Ruiz. The EEG across trials were recorded utilising the BioSemi ActiveTwo system (64 electrodes, extended international 10–20). EEG signals were referenced to the average between two electrodes affixed to the left and right mastoids. Four additional external electrodes were applied in a bipolar configuration, to capture vertical and horizontal eye-movements (EOG) and to record ECG. The data was pre-processed with the EEGLAB toolbox for MATLAB (Delorme and Makeig, 2004). First, a high pass filter at 0.05 Hz and then a notch-filter between 48–52 Hz were applied to remove power line noise. Afterwards, independent component analysis (ICA, runICA algorithm) was executed to classify artefacts (eye blinks, eye movement, cardiac artefacts).

The data were analysed and got ready to be cleaned using MATLAB. We proceed to remove the artifact of eyes blinking for each participant by individualising them on the scalp topographies. The eye artifact component can be identified based on three different characteristics:
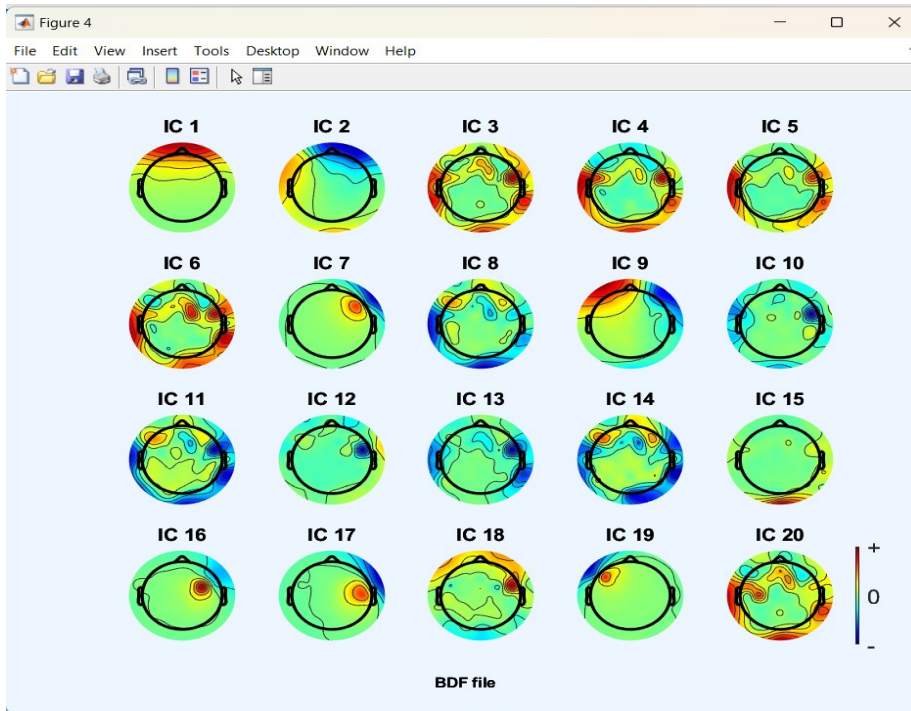
Figure 4.2, scalp topographies (Figure 5)

For instance, figure 2 shows that the component number 1 is the one that represents eye blink movement. Consequently, it has been removed. Indeed, removing eye blinks from EEG signals is crucial for ensuring the accuracy and reliability of the recorded brain activity.

4.2.7 EEG Analysis

For EEG analysis we used cluster-based permutation tests for time-frequency data which was provided by Maria Herrojo-Ruiz. A cluster-based permutation test is a statistical method used to analyse differences between two or more groups or conditions in a dataset; in our case we analysed the differences between positive and negative feedback condition. We used the Fieldtrip toolbox and a code written by Maria Herrojo-Ruiz to run a time-frequency analysis for the EEG data of each participant in the positive and negative feedback conditions.

Time-frequency analysis is a method of analysing signals that vary over time by examining their frequency content at different moments in time. This technique is often used to study oscillations in signals, which are patterns of regular and repetitive movement.

Oscillations are rhythmic patterns of movement that repeat over time, such as the beating of a heart.

These patterns can be described in terms of their frequency, which is the number of times they repeat per unit of time. For instance, a heartbeat might oscillate at a frequency of 60 beats per minute.

Time-frequency analysis allows us to see how the frequency content of a signal changes over time. This can be useful for identifying different types of oscillations in a signal and understanding how they interact with each other. For instance, in neuroscience, time-frequency analysis is often used to study brain activity and identify specific patterns of oscillations that are associated with different cognitive processes.

4.2.8 Time-frequency Analysis

Time-frequency analysis is a method used in signal processing and neuroscience to analyse how the frequency content of a signal changes over time. Time refers to the duration of the signal being analysed, whereas frequency refers to the number of cycles or oscillations that occur in a certain amount of time. In time-frequency analysis, the signal is divided into small time windows, and the frequency content of each window is analysed using a mathematical tool called the Fourier transform. This allows us to see how the frequency content of the signal changes over time. The output of time-frequency analysis is often presented in the form of a spectrogram, which is a visual representation of the frequency content signal over time. The time is showed on the x-axis and the frequency on the y-axis. The spectrogram displays the amplitude (the power) of a signal across both time and frequency, usually represented as a colour map. Time-frequency analysis can be performed using a variety of techniques, each one has it is own strengths and weaknesses.

Chapter 5: Results

The participants who took part in this research were pianists between the age of 18 years old and 65 years old, with at least six years of musical training. None of them had been diagnosed with a neurological or psychiatric or neurodevelopmental condition, and neither they had been taking any medication for depression or anxiety. This resulted in a sample of 25 participants (56%female, 44%male, mean age= 29.4 years old).

The research aimed to investigate both the behavioural and neurocorrelates results, so we had two hypotheses. The behavioural hypothesis aimed to investigate if pianists would learn faster from negative feedback instead from positive feedback. Being faster in this case means that they will be faster in adapting their future behaviours (actions) to find the hidden target dynamic and consequently they will have better scores. In other words, we expect the pianist to have better scores in negative feedback conditions. Regarding the neurocorrelates hypothesis, we predict that the better learning process during the negative feedback block will be associated with reduced beta

oscillations in sensorimotor and prefrontal brain areas. Additionally, we tried to investigate the anxiety symptoms levels with a self-report questionnaire (K-MPAI-R), to investigate if anxiety levels could be associated to a faster learning process with negative feedback.

In this study, we recruited 25 pianists (14 female, 11 males, mean age= 29.4years old) and the variable that has been manipulated is the type of feedback. The participants had to process both positive feedback and negative feedback, allowing us the infer the impact of different types of feedback on motor learning process.

5.1 Behavioural results

Regarding the behavioural analysis, the descriptive statistics for the learning rate across trials in the different feedback conditions are shown in Table 1.

Condition	Trial block	Mean	Median	Max	Min	StDev
Negative	1	44.78	48.41	79.12	0.00	19.24
	2	46.39	50.18	78.67	0.00	18.24
	3	49.91	53.82	82.39	0.00	17.86
	4	49.07	53.82	76.92	0.00	17.79
	5	49.97	53.95	92.15	0.00	18.38
Positive	1	50.57	51.53	86.99	7.69	14.27
	2	53.43	54.34	88.08	7.59	13.69
	3	55.69	56.50	90.94	12.02	13.70
	4	55.73	55.95	88.08	12.43	14.28
	5	58.01	57.33	92.76	15.03	13.55

Figure 5.1 Descriptive statistics for the learning rate across trials in the different feedback conditions (Table 1)

Table 1 shows the descriptive statistics of the sample data. The trial block, divided in 5 time point is display in the first column. The mean values of each variable are presented in the second column, indicating the central tendency of the data. The median values are also provided in the third column, which represent the middle value of the dataset when it is arranged in ascending order.

The sixth column displays the standard deviation values, which indicate the variability or spread of the data around the mean. A higher standard deviation indicates that the data points are more spread out from the mean, while a lower standard deviation indicates that the data points are more clustered around the mean. Additionally, the table provides information about the range of values for each variable. The minimum and maximum values are shown in the fourth and fifth columns.

Participants played on average 10.6 hours per week at the point of the experiment and on average they had played the piano for 10.6 years. This was assessed to evaluate how intensely they had been practicing the piano.

A two-way RM-ANOVA was employed to analyse the behavioural data.

For the RM-ANOVA, each participant's scores in the negative and positive feedback conditions were averaged across 20 trials, generating five time points at which feedback scores were assessed. A 2 x 5 design was employed in the RM-ANOVA to assess the effect of the two feedback conditions and increased trials on learning. Positive and negative feedback with 100 levels each were the two dimensions in which all participants participated. The 100 levels contained the scores given to participants after each trial. The five dimensions were the five different time points at which the average of twenty trials for each participant was measured. Trials 1–20, 21–40, 41–60, 61–80, and 81–100 were averaged into single values displaying five time points across the experiment. Before averaging, the 0 (positive feedback block) and -100 (negative feedback block) values that participants perceived when they made a pitch error were removed to avoid skewed data. The variables were entered into RStudio software for a two-way RM-ANOVA thus were 1 – 20 positive, 21 – 40 positive, 41 – 60 positive, 61 – 80 positive, 81 – 100 positive, and 1 – 20 negative, 21 – 40 negative, 41 – 60 negative, 61 – 80 negative, 81 – 100 negative. The results of a two-way RM-ANOVA are displayed in table 2.
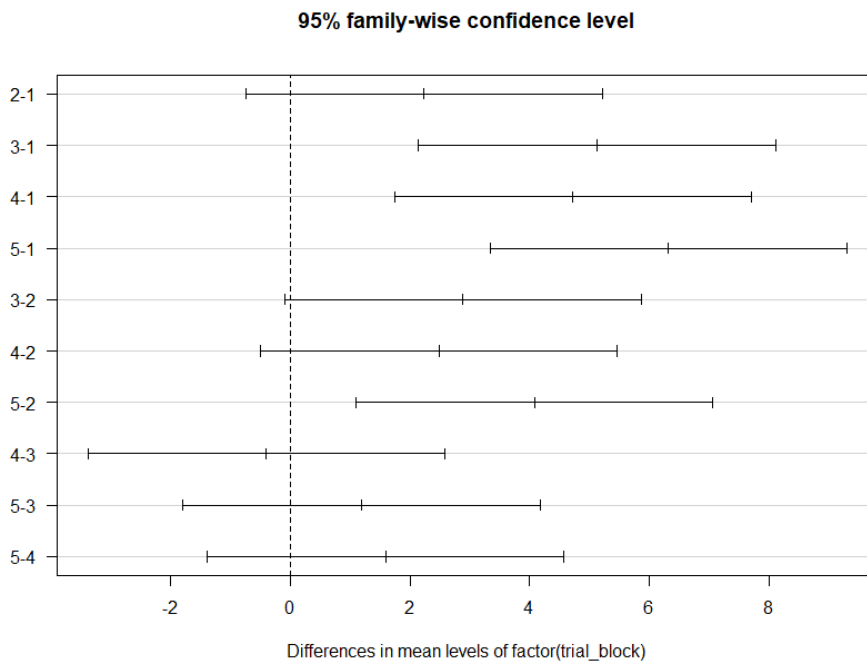
95% family-wise confidence level

Figure 5.1 Differences between mean levels in different trials (Figure 6)

The graph (Figure 6) demonstrates the statistical significance of differences between means and 95% confidence intervals for each group. To obtain the graph, we used the Tukey Test. In other words, the graph shows, for each combination of groups, the value of the difference between the means and their respective 95% CI. The vertical dashed line on the graph represents the point where the difference between the means is zero, meaning the means of the two groups are equal. If the bars representing the means of two groups overlap the vertical dashed line, then their means are not significantly different. We created an additional Table (Table 2) to inspect the p-value variable.

Trail_block	Diff	lwr	upr	p adj
2-1	2.2366795	-0.74142284	5.214782	0.1046048
3-1	5.1236055	2.14550316	8.101708	0.0109611
4-1	4.7227850	1.74468267	7.700887	0.0138550
5-1	6.3136463	3.33554395	9.291749	0.0059658
3-2	2.8869260	-0.09117633	5.865028	0.0543240
4-2	2.4861055	-0.49199682	5.464208	0.0802211
5-2	4.0769668	1.09886445	7.055069	0.0210479
4-3	-0.4008205	-3.37892282	2.577282	0.9400050
5-3	1.1900408	-1.78806154	4.168143	0.3913391
5-4	1.5908613	-1.38724105	4.568964	0.2277972

Figure 5.1 P-value results of means levels in different trials (Table 2)

Table 2 allows us to determine whether the differences are statistically significant or not. The experiment involved participants processing both negative and positive feedback at different time points, which are referred to as trial blocks. The table provides information about the differences between the mean scores of each trial block for different measures, as well as statistical significance and confidence intervals. Specifically, it shows the first column that indicates the comparison being made, such as the difference in mean scores between trial block 2 and trial block 1. As can be seen, the mean difference between trial blocks 2-1, 3-1, 4-1, and 5-1 are all positive and statistically significant (p adj < 0.05), indicating that participants processed feedback differently over time. That means that there is significant interaction effect of the independent variables (feedback conditions) on the depend variable (learning from feedback). This finding is crucial to support one of the research's goals, such as investigating the feedback's effect on learning process. The mean differences between trial blocks 3-2, 4-2, 5-2, 5-3, and 5-4 are all positive but not statistically significant (p adj > 0.05), indicating that there may be some differences in feedback processing between these trial blocks, but they are not strong enough to be considered statistically significant at the 0.05 level. This could suggest that participants need a certain time to adapt their future actions to the received feedback. Whereas the second column shows the size of the difference (i.e., the effect size) between the two trial blocks. The third and fourth columns provide the lower and upper bounds of the 95% confidence interval for the effect size, which is a measure of how certain we can be that the effect size is not zero. The last column shows the p-value, which indicates the probability of observing the effect size by chance if there is really no difference between the trial

blocks.   For
visualisation, Figure 7 displays the average scores of all participants in positive and negative
feedback across the five dimensions we created for the trials. During the experiment, the
participants had to play a melody on a digital piano, they had 100 trials receiving positive feedback
and 100 trials receiving negative feedback. The feedback was representing by a score that appeared
after each trial and remained on the screen for 1.5 seconds. We wanted to investigate if participants
got better scores during the positive conditions or the negative feedback conditions. Having better
scores could translate as they adapted their behaviour quicker to reach the desired goal, which was
get closer as possible to the hidden dynamic target.

Averaged score comparison between positive and negative condition
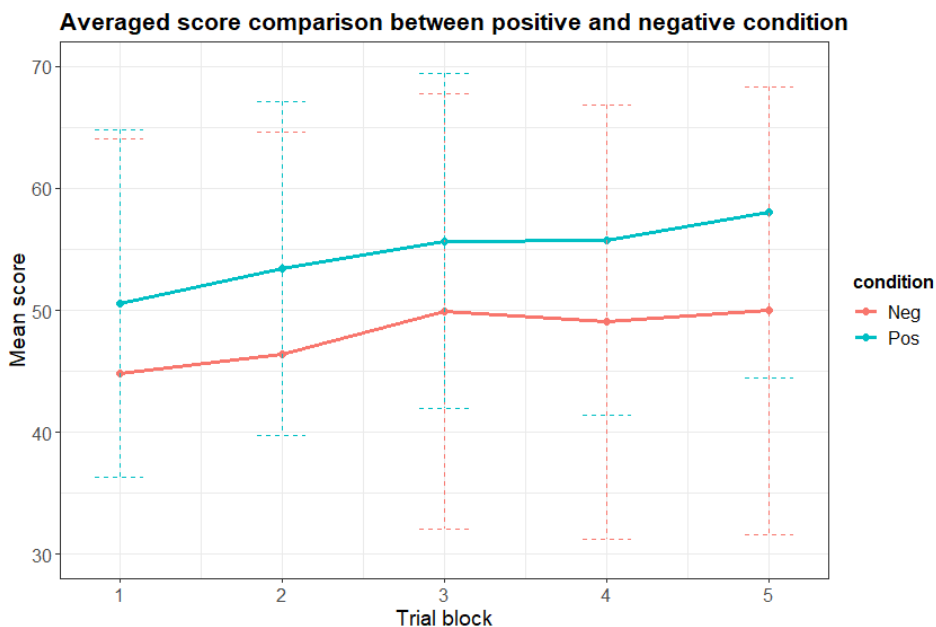
Figure 5.1 Representations of the mean scores of all participants in both conditions (Figure 7)

Figure 7 provides a visual representation of how scores change over time and across different
feedback conditions. The x-axis represents the trials, which have been divided into five dimensions
for ease of analysis. The y-axis shows the mean scores for each trial, averaged across participants.
The graph is divided into different coloured lines, each representing a different feedback condition.
By comparing the different lines, we can see how scores vary across different feedback conditions
over the course of the trials.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Factor (condition)	1	110.79	110.79	351.471	0.000331***
Factor (Trial_block)	4	51.47	12.87	40.819	0.005993**
Condition: Trial_block	1	0.85	0.85	2.682	0.200017
Residuals	3	0.95	0.32		

Figure 5.1 Representations of the results of the two-way RM-ANOVA (Table 3)

Table 3 describes presents the results of a two-way repeated-measures analysis of variance (RM-ANOVA) conducted on the data. A p-value less than 0.05 (indicates by ***) is considered statistically significant, meaning that there are significant differences between the mean scores of different trial block for some **measures**, while for others the difference is not significant. Specifically, the two variables Factor (condition) and Factor (trial_block) are significant. By Factor (condition) we mean that the manipulated variable is the feedback condition, positive vs negative by which participants got feedback while playing the piano. This variable is resulted to be significant, which mean that the condition has itself a significant effect on the performance. By Factor Trial block we aimed to investigate if participants presented a difference based on which trial block where processing. Indeed, it appeared that participants got better scores over time, as can be seen the Factor Trial block is significant, thus the variable produce a significant effect on the learning process. Contrary, the interaction between condition and trial block is not significant, this means that the feedback's effect (positive vs negative) on the participants' performance did not change significantly across different trial blocks.

Overall, Table 3 provides a summary of the results of the two-way RM-ANOVA, indicating the sources of significant variation in the data and their respective effects on the outcome variable.

5.2 EEG results

Regarding the EEG analysis only 10 participants were evaluated instead of 25, due to technological issues that occurs to incomplete data files.

Commented [MOU7]: Devi descrivere però I risultati. Cosa vogliono dire? Cosa vuol dire che il fattore effetto è sifgnificativo?

Cosa vuol dire che il fattore blocco è significativ?

For EEG analysis we used cluster-based permutation tests for time-frequency data which was provided by Maria Herrojo-Ruiz. We ran a time-frequency analysis for the EEG data of each participant in the positive and negative feedback conditions and we averaged the data of 10 participants in both positive and negative feedback conditions. we averaged to analyse the relationship between the positive and negative feedback provided to participants and their overall scores. To achieve this goal, I averaged the scores of all participants in both the positive and negative feedback conditions. This allowed me to directly compare the effect of positive and negative feedback on participants' overall scores and to assess the difference between the two conditions.

The time-frequency representation is a graphical representation of the time-varying spectral content of the data. The x-axis of the plot represents time, while the y-axis represents frequency. The intensity or colour of the plot at each point represents the power of the spectral content at that point in time and frequency. Interpreting the time-frequency representation can provide insights into the nature of the data being analysed. For example, it can help identify patterns of activity or changes in activity over time and across frequencies. It can also reveal relationships between different frequency bands and different regions of the brain or other parts of the body.

For the visualisation, the mean time-frequency analysis was calculated for each participant in both the positive feedback and negative feedback conditions, revealing the spectral power characteristics across time and frequency domains. The spectral power of a time-frequency analysis graphic shows the distribution of power, in our case beta oscillations power, across different frequencies and time intervals in a given signal. In those visualizations (Figure 8 and 9) the mean spectral power for each participant was calculated separately for both positive and negative feedback conditions, allowing for a comparison of spectral power between those conditions. The use of a color-coded legend allows viewers to easily identify regions of high and low spectral power, where the yellow colour reflects beta oscillations exhibiting greater amplitude, while the blue colour reflects a weaker beta oscillations' amplitude. The labels for the axes indicate the frequency range and time period covered in the analysis. The patterns of spectral power observed in the visualization can provide insights into the neural processes underlying cognitive and affective responses to positive and negative feedback.
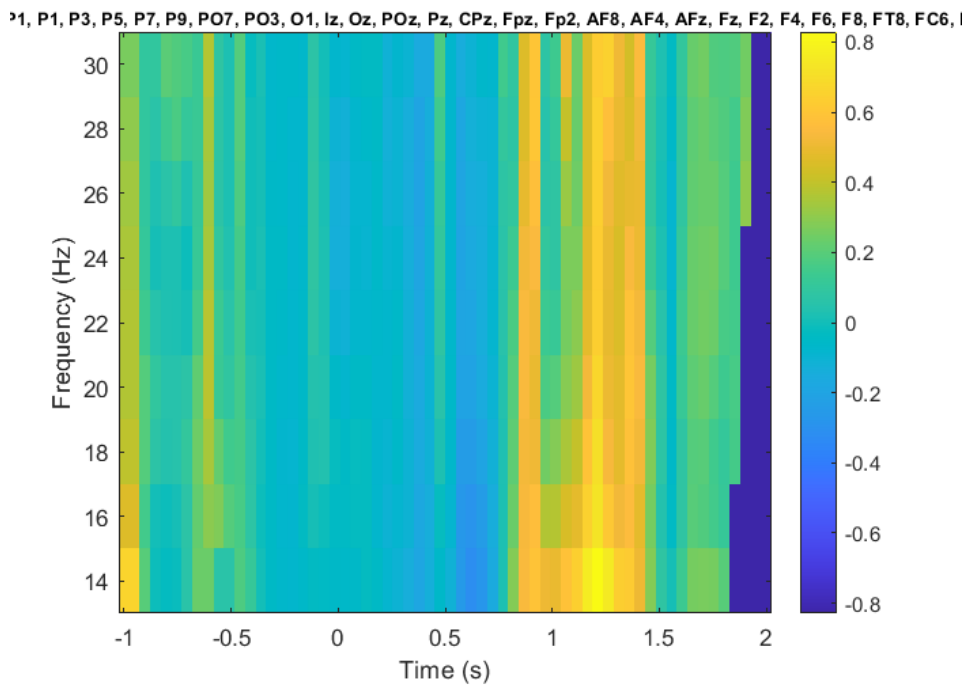
Figure 5.2 Representations of the mean time-frequency analysis in positive feedback condition (Figure 8)

The figure shows a time-frequency representation of the EEG data collected from participants during the positive feedback condition. The x-axis represents time (in seconds), and the y-axis represents frequency (in Hertz). Figure 8 allows us to see that there is an increase in beta oscillations power around 13-20 Hz in the time interval 1.2 to 1.3 s after stimulus onset.
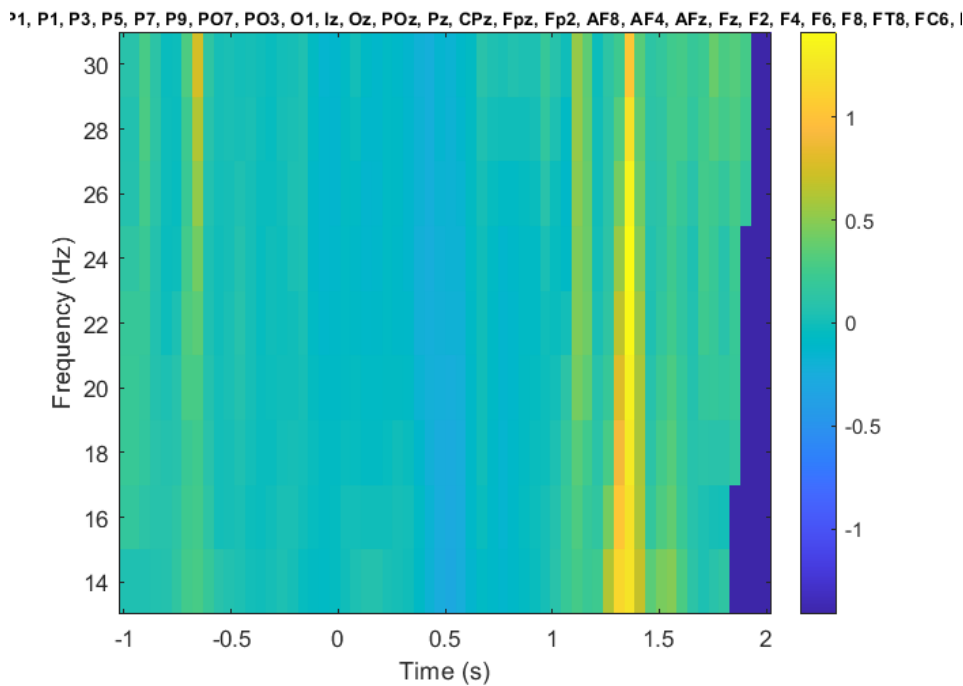
Figure 5.2 Representations of the mean time-frequency analysis in negative feedback condition (Figure 9)

Figure 9 displays an increase in beta power around 13-25 Hz in the time interval 1.3 to 1.4 s after stimulus onset. The Figure 9 shows beta oscillations increased amplitude in a smaller window compared to the positive feedback condition, but the intensity of the amplitude is higher. That means the beta oscillations during the negative feedback condition are not associated with a reduction in beta oscillation power.

5.3 Discussion

The purpose of this study was to assess feedback processing and motor learning in pianists.
The hypothesis was that pianists would learn faster from negative feedback than from positive feedback and that this accelerated learning rate in negative feedback would be mediated by lower beta oscillations.
Another goal was to see if trait music performance anxiety is related to changes in beta oscillations. However, this element had to be removed due to limitations, which will be discussed in a later section and thus we were unable to assess anxiety levels as planned.

41

The initial hypothesis must be dismissed. In contrast to previous research, this study found that pianists learn faster when they receive positive feedback rather than negative feedback. However, to determine whether there is a significant effect, we need a larger sample size. The findings are surprising and warrant further research with a larger sample size, but they do suggest that pianists process feedback and adapt their motor performance differently depending on the type of feedback they are processing. Previous research in feedback processing suggested that pianists have a negative learning bias and learn faster when given negative feedback (Müller-Pinzler, Czekalla, Mayer, & al., 2019; Sporn et al. 2020; Galea et al. 2015).

The current study's findings suggest that positive feedback accelerates learning in pianists, in contrast to the findings of Galea et al. (2015), who discovered that negative feedback accelerates learning in the general population. However, since the sample size is not sufficient to be representative the conclusions drawn from the data are speculative.

The outcomes of the two-way repeated measures ANOVA revealed that the feedback conditions had a significant fixed trial effect. This means that the participants' scores improved as the experiment progressed, so participants' scores improve as the experiment progresses. Furthermore, there is a significant interaction effect of trial condition: thus, the relationship between trial and score is conditional (positive vs negative feedback). The interaction effect is the effect of combining the independent variable (condition) and the dependent variable on the dependent variable (learning from feedback). The main effect on the learning rate is significant. The overall effect of each independent variable (positive feedback vs negative feedback condition) on the dependent variable is referred to as the main effect (learning from feedback).

From Figure 6 that demonstrates the statistical significance of differences between means and 95% confidence intervals for each group, we can see that the difference between trial 1 and trial 2 is not significant, whereas the difference between trial 1 and trial 3 is significant as well between trial 2 and trial 5. The lack of a significant difference between trials at the first time point may imply that participants required some adaptation or familiarization before meaningful changes in the measured outcome could be inferred.

According to the two-way RM-ANOVA results (Table 3), positive feedback has a higher overall mean score, implying that positive feedback accelerated pianists' learning rate. This is supported by both Table 1, which shows the mean score in both positive and negative feedback conditions and Table 2, which allows us to see the difference in mean scores between different trial blocks. One reason why pianists may benefit more from positive feedback is that musicians are typically taught through negative feedback, particularly in a professional setting (McPherson, Blackwell, & Hattie, 2022). This may result in overexposure to negative feedback, causing pianists to no longer perceive

negative feedback as essential. Individuals must perceive negative feedback as more important for a negative learning bias to apply (Shabel et al. 2014; Hoang & Sharpe, 2021; Dolguikh et al. 2021), but if overexposure to negative feedback diminishes the perceived essentiality, the negative learning bias would not apply. Positive feedback on the other hand is less used in professional music environments, which could increase its perceived essentiality, leading to a positive learning bias. Another factor that could weigh into the observed results is stress. While we were not able to assess the Music Performance Anxiety level, as originally planned, previous research suggests that professional musicians always experience a degree of stress when performing (Kenny, 2004).

It is interesting that during the negative feedback condition participants improve more steadily across trials than during positive feedback condition. Indeed, the mean score in negative feedback condition remain steady at 49 for trial 3, 4 and 5. This could suggest that negative feedback leads to steady improvement without fallout. Nevertheless, this could also be related to the lack of variability, since participants did explore less and overall scored within the same range throughout the experiment.

Previous research has shown that low-power beta oscillations are engaged in updating actions according to feedback (Yaple et al. 2018; Galea et al. 2015). Sporn et al. (2020) observed that this process is disrupted in individuals with state anxiety, where high power beta oscillations decreased the learning rate in a motor learning task. Based on this we hypothesized that an accelerated learning rate in the negative feedback condition is associated with decreased beta power. We expected to find that the positive feedback condition elicits increased beta power levels. However, the beta oscillations' amplitude seems to be more powerful during the negative feedback condition. It appears that the results contradict the hypothesis that participants will have reduced beta power in the negative feedback condition. The wider range of intensity values in the negative feedback condition (-1 to 1) (Figure 9) suggests that there is actually higher amplitude in beta power across trials in this condition compared to positive feedback condition. Since our hypothesis predicted that during negative feedback processing, participants would present reduced beta oscillations, the hypothesis must be rejected. This research hypothesis was supported by two essential findings previous studies that found out that people learn faster with negative feedback (Galea et al. 2015) and that beta power has been associated with reduced learning from feedback, thus more beta power during feedback processing cause a slower learning process (Sporn et al. 2020).

Meanwhile, the more consistent beta power across trials in the positive feedback condition, as evidenced by the narrower range of intensity values (-0.8 to 0.8) (Figure 8) and the predominance of the colour yellow, suggests that participants are experiencing more stable or consistent beta oscillations in response to positive feedback.

43

It is possible that the wider range of beta power in the negative feedback condition is related to other factors, such as increased uncertainty or variability in the task demands or in participants' responses to negative feedback.

These EEG findings are in line with the behavioural data results. After determining that pianists learned accelerated from positive feedback, we expected beta power to be more suppressed following positive feedback. It is possible that with a larger sample size the data will look different. More research with an increased sample size is necessary to draw significant results that are applicable to the general population of pianists.

5.4 Limitations

This project faced several limitations.

Firstly, we looked at a specific population: professional pianists between 18 and 65 years old, with no prior diagnosis of psychiatric or neurological illnesses, not taking anxiety inhibiting medication, and they must have played the piano for at least six years. Due to this, we had to exclude several pianists who did show interest in the experiment. Secondly, the sample used to develop this research is certainly too small, thus the experiment should present a larger sample size. Thirdly, we did not proceed to assess anxiety levels with the MPAI-R as planned. Indeed, the questionnaires still had to be reprocessed, and the reprocessing of the data took longer than expected, so they couldn't be included in the research data.

5.5 Implications for Future Research

The findings of this project have implications for future research.

It'll be interesting to see if this project is expanded to include previously planned dimensions like trait music performance anxiety. It would be interesting to see whether professional pianists experience MPA despite their familiarity with performance settings, and whether it acts as an inhibitor or accelerator for their motor learning rate in dichotomous feedback conditions.

The current findings only look at professional pianists as a whole, with no distinction between high and low MPA scores. While previous research suggests that trait anxiety speeds up belief updating after negative feedback (Fan et al. 2020), it is important to determine whether this also applies to professional pianists with trait MPA. Especially since the outcomes of this study suggest that professional pianists react significantly different to negative feedback than the general population, which was found to show accelerated learning rates following negative feedback (Galea et al. 2015).

It might also be interesting to look into the population differences between pianists and non-musicians.

While beta oscillations and their effect on motor performance are still being studied, these findings suggest that there are differences between musicians and the general population when it comes to updating beliefs in response to dichotomous feedback.

Pianists were chosen for this study because piano dynamics are more variable and can be manipulated more easily than in other instruments. Future research should consider broadening the scope to include other types of professional musicians. It may be worthwhile to examine the differences between classical, jazz, and popular music musicians in this context, as the environments in different musical genre environments may influence feedback processing regarding their performance.

It might be interesting to design such an experiment with a large sample size in order to obtain meaningful results for a population. It would also be interesting to be able to calculate anxiety levels using other methods other than self-report questionnaires. Indeed, it is well known that self-report questionnaires can produce untrustworthy results. In fact, because the K-MPAI-R is a self-report questionnaire, the result dependent on the honesty and accuracy of the respondent's answers. In future research, it would be appropriate to investigate anxiety levels with more statistical tools and it would also be interesting to see whether anxiety levels are associated with reduced beta power in sensorimotor and prefrontal areas. Indeed, it has been discovered that anxiety has a strong influence on beta power.

5.6 Conclusion

According to the descriptive statistics, positive feedback has a higher overall impact.

Overall, it appears that pianists update their motor learning beliefs with a positive learning bias. According to behavioural data, during the positive feedback condition, participants explored more and scored higher overall. The distinction between the two conditions is significant.

The neural data results are consistent with the behavioural data results, with beta power increasing in the negative feedback condition rather than the positive feedback condition, as supported by the literature. While these findings are consistent with previous research and what we expected to find, they are surprising because behavioural data would suggest that beta power would be suppressed following positive feedback.

A speculative approach to these findings could be to investigate whether pianists have a positive learning bias and how they react to increased beta power differently than the general population. This would be interesting to investigate further in future research, where a larger sample size could yield more conclusive results.

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