Neural Correlates of Valence-dependent Augmented Feedback Processing in Extensive Motor Learning

Cumulative Dissertation

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Abstract

Motor automaticity is important to enable a stable performance. The process of automatization is affected by the valence of augmented feedback during practice. Although research has been conducted from the behavioral side on the scheduling of augmented feedback, the underlying neural mechanisms are not yet entirely clear. A deeper understanding of these mechanisms may help to design optimal feedback conditions for motor learning. Several neural correlates are associated with valence-dependent feedback processing but have mainly been studied in the cognitive domain. The aim of this dissertation is to examine distinct neural correlates (feedback-related negativity, P300, late fronto-central positivity, frontal theta-band activity) during the process of extensive motor learning. Therefore, participants learned an elbow-extension-flexion sequence with three movements reversals in five practice sessions (192 trials each) with subsequent feedback presentation. EEG was recorded during the first and the last practice. The degree of motor automatization was tested in a pre-test-post-test design using a dual-task paradigm. It could be shown that feedback providing error information provoked activity across frontal neural correlates, this can be interpreted as higher attention-dependent processing. Well, several learning theories assume that such processes are likely to decrease with further practice and an increasing amount of automatic control. This could only partly be confirmed by the current results. Although many questions remain unanswered, this dissertation provides insights to neural activity underlying feedback-based motor learning that offer some aspects for follow-up research.

Zusammenfassung

Eine automatisierte Bewegungsausführung ist wichtig für eine stabile Performanz. Der Automatisierungsprozess wird von der Feedbackvalenz während des Übens beeinflusst. Die zugrunde liegenden neuronalen Mechanismen sind allerdings noch nicht geklärt. Ein besseres Verständnis dieser Mechanismen kann bei der Gestaltung von optimalen Feedbackbedingungen für motorisches Lernen helfen. Einige neuronale Korrelate werden in Bezug auf die Verarbeitung von valenzabhängigem Feedback diskutiert, sind bisher aber eher im kognitiven Bereich erforscht worden. Das Ziel dieser Dissertation liegt darin, ausgewählte neuronale Korrelate (‚*feedback-related negativity*', P300, ‚*late fronto-central positivity*', frontale Theta-band Aktivität) während des extensiven motorischen Lernens zu untersuchen. Die Versuchspersonen übten eine Ellbogen-Streck-Beuge-Sequenz bestehend aus drei Umkehrpunkten über fünf Übungseinheiten (je 192 Trials) mit nachfolgender Feedbackgabe. Ein EEG wurde in der ersten und letzten Übung aufgenommen. Der Grad motorischer Automatizität wurde anhand eines Doppeltätigkeitstest in einem Pre-Post-Test-Design bestimmt. Es konnte gezeigt werden, dass ein Feedback welches Fehlerinformationen transportiert, Aktivität in frontalen neuronalen Korrelaten bewirkt. Dies wird als erhöhte attentionale Verarbeitung interpretiert. Verschiedene Lerntheorien postulieren, dass solche Prozesse mit weiterer Übung und zunehmender Automatizität abnehmen. Dies konnte nur teilweise durch die vorliegenden Ergebnisse bestätigt werden. Diese Dissertation gibt Einblicke in die neuronale Verarbeitung valenzabhängigen Feedbacks beim motorischen Lernen und liefert Ansätze für weitere Forschungen.

Contents

List of Publications

Peer-reviewed Journal Articles

Margraf, L., Krause, D., & Weigelt, M. (2022). Valence-dependent neural correlates of augmented feedback processing in extensive motor sequence learning – Part I: Practice-related changes of feedback processing. *Neuroscience*, *486*, 4-19. https://doi.org/10.1016/j.neuroscience.2021.04.016

Margraf, L., Krause, D., & Weigelt, M. (2022). Valence-dependent neural correlates of augmented feedback processing in extensive motor sequence learning – Part II: Predictive value of event-related potentials for behavioral adaptation and learning. *Neuroscience*, *486*, 20-36. https://doi.org/10.1016/j.neuroscience.2021.04.018

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Oral Presentations

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Margraf, L., Krause, D., & Weigelt, M. (2022). Examining the Neural Processes of Valence-Dependent Feedback Processing and Practice-Related Changes in Extensive Motor Learning. In C. Voelcker-

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Abbreviations

ABC	Anticipative Behavioral Control
ACC	anterior cingulate cortex
AE	absolute error
AIC	anterior insular cortex
BAC	basic action concept
c.f.	compare to (Latin “*confer*”)
CNV	contingent-negative variation
DLPFC	dorsolateral prefrontal cortex
dPMC	dorsal premotor cortex
DTC	dual-task costs
EEG	electro-encephalogram
e.g.	for example (Latin “*exempli gratia*”)
EPAC Hypothesis	Error-Provoked-Attentional-Control Hypothesis
ERP	event-related potential
et al.	and others (Latin “*et alii*”)
FBO	feedback onset
FB-LPP	late-positive potential
FB-P3	feedback P300
FRN	feedback-related negativity
ibid.	at the same place (Latin “*ibidem*”)
i.e.	that is (Latin “*id est*”)
IFJ	inferior frontal junction
KP	knowledge of performance
KR	knowledge of results

LFCP	late fronto-central positivity
M1	primary motor cortex
maxAE change	change of the maximum absolute error
ms	milliseconds
n.d.	no date
neg.	negative
P1	Practice 1
P5	Practice 5
PFC	prefrontal cortex
PMd	dorsal premotor cortex
PMv	ventral premotor cortex
pos.	positive
PPC	posterior parietal cortex
preSMA	pre-supplementary motor area
rewP	reward positivity
RP	readiness potential
RPE	reward prediction error
S1	primary somatosensory cortex
SAE	situation-action-effect
SDA – M	Structural Dimensional Analysis – Motoric
SMA	supplementary motor area
SPN	stimulus-preceding negativity
TEC	Theory of Event Coding
VE	variable error

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PART I – SYNOPSIS

1 Introduction

Human beings interact with their environment through their ability to execute goal-directed movements (actions), e.g., speaking, gesturing, or object manipulation. That is, human beings not only respond to a perceived stimulus (the sensorimotor principle) but want to achieve a predetermined goal (the ideomotor principle) (e.g., Hommel & Nattkemper, 2011). An action is focused on the voluntary achievement of a specific outcome (e.g., Hoffmann & Engelkamp, 2013; for more details on how to describe human actions, see Prinz, 2014)[1]. In other words, the anticipated outcome of an action determines the action to be executed:

One usually does not reach for a glass of water to drink as a reaction to the perception of a glass of water standing on the table. With the desire to drink something, one explores the environment for a corresponding possibility to fulfill this need. Or one does not throw a basketball towards a basket because a basket is perceived. If someone is familiar with the game of basketball and the corresponding rules, the person knows that points can be scored if the ball hits the basket.

The outcome of an action can be experienced by its effects in the environment and is then associated with this action (e.g., Rescorla, 1991). The perceived outcome enables an evaluation of the executed action with respect to the desired outcome (action goal) and, therefore, modulates human behavior in terms of behavioral adaptations when the action's goal is not achieved (*Anticipative Behavioral Control* [ABC theory], Hoffmann, 2003). The information about whether an action's goal has been achieved or not can be interpreted as a source of feedback. The perceptible outcome of an action can either be recognized by one's own sensory systems (e.g., visual, auditory, proprioceptive, tactile), or can be reported back from an external source (for example another person or a video recording) (e.g., Magill & Anderson, 2014). Based on the described interaction of an action's goal, its anticipated outcome, and feedback, human beings can experience their environment, can learn from it, and can further modify or manipulate it:

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[1] The term 'action' has to be distinguished from the term 'behavior', which refers to all activities of an organism, including voluntary movements, but also involuntary reflexes (APA Dictionary of Psychology, n.d.).

There are two buttons on the wall. Wanting to switch on the lights, the right button is pushed. As a result, the lights come on. If the button is being pushed for the first time, the agent realizes that the lights can be turned on by pressing a button. With respect to the left button and based on what was acquired from the right button, the agent may also expect to be able to turn on the light by pressing it. There are two possibilities: Either this expectation can be confirmed, and the lights also come on after the left button is pressed, or it is not, and something else happens, for instance, the doorbell rings. In the latter case, the agent would look for the source of the mistake. Why was the expectation not confirmed? It can be concluded that pressing the right button turns on the light, while pressing the left button rings the doorbell. Whether these associations truly fit must now be confirmed by several tests and trials. Over time, the agent learns which button elicits which effect.

In addition to the movements to be executed, an action is always linked to its predetermined goal (the outcome of the action), which can be perceived after the execution. The action and the corresponding outcome are accordingly assumed to be stored in a common cognitive representation (*Common Coding Theory*, Prinz, 1990). The integration of the intention of the acting person (the action's goal), the corresponding movements, and their outcomes are described in the *Theory of Event Coding* (TEC, Hommel et al., 2001), which makes an attempt to replace the classic stimulus-response model and addresses the question of how action goals are translated into behavior, rather than placing the stimulus at the beginning of the process (Hommel & Nattkemper, 2011). However, it should be noted that motor learning goes beyond a categorical assignment of an action and its outcome in dependence of an action goal. With respect to the movement itself, temporal and dynamic aspects must also be learned. To take up the example of pressing a button mentioned above:

The agent does not only learn which button provokes which effect. The agent must find the optimal movement trajectory to bring the arm towards the button and find the appropriate acceleration to hit the button. Next, the application of the hand must be considered: Which and how many fingers must be used? Or even the whole hand? When, during the arm movement, the hand should be moved into the appropriate position? Once the switch is reached, the agent must decide where exactly to place the fingers (or the hand) on the switch, and how much force must now be applied to exert the appropriate pressure on the button.

The association between an action (including all its temporal and dynamic aspects) and its perceptible outcome encoded in a common representation can be assumed to be a dynamic process. The established associations must be checked for correctness with every successive execution of that action and must be updated, if necessary. An action whose execution is based on motor practice can be defined as a motor skill (Schmidt & Lee, 2011). Therefore, it can be said that humans are challenged with the learning of new motor skills or with the adaptation of already learned movement patterns throughout their whole lifespan whether in sports (e.g., learning a new skill or technique), in rehabilitation (e.g., after injury or stroke), or in daily life (e.g., handling a new device). In this regard, the level of perfection to which a motor skill can be internalized with an extensive amount of practice (e.g., in competitive sports or playing an instrument) is quite remarkable.

The process of learning a novel motor skill proceeds through various phases and can support motor automatization – as a dimension of learning. Motor automatization is characterized by a reduction of attention-dependent processing (e.g., Chein & Schneider, 2012; Hikosaka et al., 1999) which is which is a prerequisite for a stable performance, for example, in competitive sports but also in daily life (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). Usually, motor practice is accompanied by external feedback to support the learning process, for instance, from another person like a coach or a therapist, but also other sources like video recordings (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation). Therefore, feedback is an essential tool to support motor skill learning, and moreover, the feedback valence during the practice intervention notably moderates the learning process (e.g., Krause & Blischke, 2023; Wulf et al., 2010). In this context, attentional control is thought to be elicited by feedback of negative valence, as a result, negative feedback is assumed to disrupt processes of motor automatization (*Error-Provoked-Attentional-Control Hypothesis* [*EPAC Hypothesis*]; Krause et al., 2018). It can be concluded that motor learning is a result of a complex interplay of different mechanisms (e.g., action planning, action execution, feedback processing), which might change with further practice.

All this is enabled by the brain, which is *"among the most complex structures in nature"* (Gluck et al., 2008; p. 44). While different feedback designs and their impact on motor learning are relatively well researched from a behavioral perspective (for reviews, see: Salmoni et al., 1984; Swinnen, 1996; Wulf & Shea, 2004), still very little is known about the cognitive mechanisms during motor skill learning in interaction with feedback processing. A deeper understanding of these mechanisms is important to design optimal learning conditions, whose effects can be explained from a neurophysiological point of view (e.g., for patients in rehabilitation after brain injury, but also for the design of augmented feedback conditions in leisure activities, and recreational and competitive sports).

Since motor skills are quite different in their nature and characteristics (e.g., discrete, serial, and continuous skills; Schmidt & Lee, 2011) there is the question whether they all depend on the same neural mechanisms or if differences exist. In this context, Krakauer and colleagues (2019) provide an overview of motor tasks that are used to examine motor skill learning, e.g., motor sequence learning, motor adaptation, or motor acuity. While motor sequence learning (defined as the learning of the order of successive actions; e.g., Dahm et al., 2023a; Dahm et al., 2023b) and motor adaptation (defined as the ability to adapt motor commands to a changing environment; e.g., Lex at al., 2014) have been widely studied with respect to the underlying neural mechanisms (for a review, see Krakauer et al., 2019), the learning of motor acuity (defined as the accuracy and consistency with which an action can be performed once it was selected, e.g., Agethen & Krause, 2016; Krause et al., 2018) has received less attention (Krakauer et al., 2019). While motor sequence learning and motor adaptation refer to the correct selection of a movement, and motor acuity relates more to the performance of a selected movement (ibid.), differences in the neural mechanisms underlying these tasks may exist. For example:

Writing a series of different letters as a motor sequential learning task (e.g., a b c d) depends on the correct choice of the next letter after the first one is written. Writing the same letter (e.g., a) in different sizes depends on the choice of the right proportions and their adaptation to the environmental conditions (e.g., lines on a sheet of paper). However, reproducing the same letter (e.g., a) several times in the same size and appearance with as little variation as possible depends on a greater level of accuracy and on the consistency of the underlying movement pattern.

Several neural correlates are discussed in relation to augmented feedback processing and are associated with distinct learning mechanisms, but these are primarily in the cognitive domain (e.g., visual categorization task: Krigolson et al., 2009; paired-associate learning task: Arbel et al., 2014; for a review, see Walsh & Anderson, 2012). In the meanwhile, there is a growing number of studies that have examined the neural processing of augmented feedback in the motor domain (e.g., discrete arm-movement sequence: Krause et al., 2020; goal-directed throwing: Frömer et al., 2016; Joch et al., 2018; Maurer et al., 2019). In this context, the study of Krause and colleagues (2020) could measure three event-related potentials (ERPs) as response to the presentation of valence-dependent augmented feedback: the Feedback-Related Negativity (FRN), the P300, and the Late Fronto-Central Positivity (LFCP). However, research on learning effects is lacking. This dissertation aims to support the research of the neural processing of augmented valence-dependent feedback in the motor domain with respect to a motor task, which depends on the learning of accuracy and consistency in the performance of a motor sequence. Therefore, the valence-effects of selected ERPs (i.e., FRN, P300, LFCP) should be replicated and extended due to practice-related changes in the processing of feedback after an extensive practice phase. Based on this, another focus will be on the predictive value of those ERPs for short-term behavioral adaptations (goal-directed, goal-independent) and long-term learning effects (retention performance, automatization). Since an ERP only represents the part of the neural signal that is time- and phase-locked to the stimulus (e.g., Cohen, 2014), further insight into the cognitive processes is promised from an additional investigation of selected frequency-band activity. Previous research has shown that, in particular, activity in the frontal theta-band has been associated with valence-dependent feedback processing (e.g., Cavanagh et al., 2010, Lange & Osinsky, 2021).

In the following, this synopsis is divided into two further chapters. Chapter 2 deals with the principles of motor learning, including a definition of motor learning, a theoretical background with respect to learning and memory, the phases of motor learning, a discussion of augmented feedback as a moderating factor, and the neural basis of feedback processing in motor learning. Chapter 3 will explain the present dissertation project, including selected methodological considerations, the aim of the current study, an explanation of the sequence-learning experiment, the hypotheses, a summary of important results, and a general discussion with limitations, conclusions, and future direction. The three papers that emerged from the current study can be found in the cumulus (Part II) of the present dissertation.

2 Principles of Motor Learning

We are born to move, but learn to move skillfully.

Magill & Anderson, 2014, p.2

2.1 Definition

The ability to produce goal-directed movements (actions) is crucial for daily human life. Such actions require voluntary movement control to achieve the defined goal (Magill & Anderson, 2014). Actions, "*that are dependent on practice and experience for their execution, as opposed to being genetically defined*" (Schmidt & Lee, 2011, p. 499) are called 'motor skills'. According to Weigelt and colleagues (2023, p. 42), "*learning refers to a relatively permanent change in a person's behavior or behavioral potential, based on experience and knowledge acquisition*". The process of motor learning is not apparent, it can only be verified by an observable change of behavior, and can, therefore, be seen as consequence of practice (e.g., Magill & Anderson, 2014; Schmidt & Lee, 2011; Weigelt et al., 2023).

Since motor learning cannot be observed directly, there must be methods to objectively evaluate behavioral changes that indicate learning has taken place. In this context, it is important to differentiate between the terms, 'performance', 'acquisition', and 'learning' (Schmidt & Lee, 2011). The term 'performance' refers to the outcome of an action (execution of a motor skill) restricted to one specific time in a specific situation, for example, a single trial in a practice session (e.g., Magill & Anderson, 2014; Schmidt & Lee, 2011). The term 'acquisition' refers to the improvement of performance from the beginning to the end of one practice session and, therefore, to short-term behavioral changes (e.g., Olivier et al., 2013). The term 'learning' refers to retention performance that is assessed after a consolidation phase (ibid.). In the following, 'learning' is referred to when there is at least one night of sleep between a practice session and the retention test. Sleep is thought to be essential for the consolidation of memory and offline learning effects, as new knowledge is strengthened (Erlacher et al., 2012).

Magill and Anderson (2014) defined six characteristics of motor skill learning: (1) The performance of a motor skill improves with practice, for example, the performance becomes more accurate. (2) The performance is less variable and more consistent from trial to trial. (3)

The performance becomes more stable with respect to internal or external perturbations. (4) The improvements are persistent and long-lasting. (5) The performance of the motor skill can be adapted to a changing environment or different situations. (6) The performance of the motor skill demands less attentional resources.[2]

2.2 Learning and Memory

A construct that is closely related to learning and, by consequence, also to motor skill learning, is memory. During the learning progress, new memory contents are stored so that they can be remembered, or in cases of motor skill learning, can be applied in suitable situations. In this chapter section, the psychological concepts of learning and memory will be discussed in more detail.

2.2.1 Learning Principles

Learning is associated with the acquisition of new knowledge or new behavioral patterns (e.g., motor skills), but also includes the forgetting of content when it is no longer needed (Weigelt et al., 2023). In the following, the focus will be on how humans can acquire new motor skills. According to the Behaviorism (based on John B. Watson, 1913), it has long been assumed that behavioral memory occurs due to the formation of stimulus-response associations (cf., Hoffmann & Engelkamp, 2013; Thompson, 2012). It was simply believed that if elements or events occur close together in time, they are related to each other (Thompson, 2012). Two mechanisms that are based on this assumption should be mentioned here: classical conditioning (Pawlow, 1953) and operant conditioning (Skinner, 1938). The approach of classical conditioning assumes that a former neutral stimulus is associated with a pre-existing, conditioned, stimulus-response connection (cf., Weigelt et al., 2023). As a consequence, the reaction that originally followed the conditioned stimulus already occurs as soon as the former neutral stimulus is perceived (cf., Hoffmann & Engelkamp, 2013; Thompson, 2012). Among the most famous examples here are the experiments of Iwan O. Pawlow (1953) in which a previously neutral stimulus (the sound of a bell) was presented to a dog simultaneously with the presentation of food (which, as a conditioned stimulus, triggered

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[2] The concept of attention is very broad and may be defined as limited capacity, as alertness, or as selective attention (Posner & Boies, 1971). In the current dissertation, attention (or attentional resources) is understood as a limited cognitive capacity of the working memory for information processing (cf. Chapter 2.2.2).

salivation). After several repetitions, the sound of the bell alone was enough to trigger salivation, even without the presentation of food. The sound of the bell was associated with the appearance of food, so both stimuli elicit the same response (cf., Hoffmann & Engelkamp, 2013; Thompson, 2011; or Weigelt et al., 2023).

The work of Edward L. Thorndike (1898) involves the valence of stimulus-response associations. His *law of effect* states that, if a reaction in a distinct situation repeatedly leads to a positive consequence, this stimulus-reaction connection is strengthened and the reaction is then chosen more often, compared to situations in which a reaction leads less often to a positive consequence (cf., Weigelt et al., 2023). This assumption was based on a series of experiments during which the behavior of cats trying to get out of a cage was observed. When they found food outside of the cage, the cats directly chose the right way to free themselves after a few attempts. However, if the reward (food) was absent, the cats stopped choosing the corresponding correct behavior (Thorndike, 1898; cf., Weigelt et al., 2023). Based on this approach, which can be classified as operant conditioning (or instrumental learning), Burrhus F. Skinner (1938) developed a paradigm that is known as the Skinner box. Using this box, the behavior of certain animals (e.g., rats) could be conditioned via rewarding (e.g., food or water) and punishing (e.g., mild electric shocks) stimuli, without the intervention of an experimenter (cf., Hoffmann & Engelkamp, 2013; Weigelt et al., 2023).

However, these approaches that were based on stimulus-response associations cannot explain the learning of human goal-directed behavior (i.e., actions). Such actions are always based on a certain intention, an action goal (Hommel & Nattkemper, 2011), which implies that before an action is performed, a certain outcome of that action is expected. This is described in the ABC framework by Joachim Hoffmann (1993), which states that a situation-action-effect (SAE) triple is built and strengthened if the action-effect association leads to the desired action outcome (cf., Weigelt et al., 2023). In contrast to the assumptions described above (classical and operant conditioning), human motor control is not focused on a certain stimulus, but on the anticipated goal of the corresponding action (Hoffmann & Engelkamp, 2013). A successful execution of an action is, therefore, not evaluated by a following reward or punishment, but by a comparison of the actual movement outcome with the anticipated one (ibid.).

However, not only can action-effect associations be acquired by performing an action and perceiving its outcome in the environment, but also by watching another person performing that action and observing the corresponding outcome. This is called observational learning (cf., Weigelt et al., 2023). A prerequisite for observational learning based on models is the ability to imitate a certain behavior, defined as "*the spontaneous imitation of an unfamiliar behavior, which is expressed in the reproduction of an observed movement or action effect*" (Weigelt et al., 2023, p. 46). Learning based on imitation primarily takes place during early development (e.g., newborns' imitation of the facial gestures of adults [Meltzoff & Moore, 1977]) (cf., Hodges et al., 2007; Thanikkal, 2019). However, observational learning differs from pure imitation (which usually occurs spontaneously, e.g., adopting the same posture of a counterpart [e.g., Chartrand & Bargh, 1999]) in so far as a conscious decision is made with regard to which behavior should be imitated, and which not (Weigelt et al., 2023). The ability to imitate the behavior of others is more complex than it first appears. According to the *social cognitive theory* by Albert Bandura (1977), the model's behavior must be perceived (attention) and stored (retention). Furthermore, the person must be able to perform the behavior itself (reproduction) and must want to do so (motivation) (cf., Weigelt et al., 2023). In a sports context, demonstrations are a common method used to convey information to the athlete (Williams & Hodges, 2005).

The concepts described so far all – more or less – describe processes of explicit learning, i.e., learning that is based to a great extent on conscious processes. However, motor learning can also occur unconsciously and incidentally, which is defined as implicit learning (Weigelt et al., 2023; Williams, 2020). "*Implicit learning refers to the process of learning without intention, and even without awareness of what has been learned*" (Williams, 2020; p. 255). This kind of learning can be observed in first- or second-language learning (e.g., children can speak their native language correctly before they learn the corresponding grammar in school) (cf., Weigelt et al., 2023; Williams, 2020), but also in the acquisition of motor skills (e.g., learning how to ride a bike) (Williams, 2020). The study of implicit learning in real-world skills can be challenging (Williams, 2020), however, tasks like artificial grammar learning (e.g., Reber, 1989) or motor sequence learning (Nissen & Bullemer, 1987) have proven suitable. With respect to motor skill learning, implicit learners have little verbal recallable knowledge about the movement as compared to explicit learners (e.g., Maxwell et al., 2001). It could be shown that both implicit and explicit learning result in comparable retention performances, but implicit learning leads to more stable performance in cognitively demanding situations (e.g., stress) as compared to explicit learning (ibid.).

2.2.2 Memory

As previously mentioned, learning is characterized by the storage of new knowledge and the forgetting of knowledge that is not needed anymore. Therefore, memory plays a crucial role for learning in general, as well as for motor learning. Up to now, different concepts and assumptions of motor learning have been presented here. In the following, the general concept of the psychological construct of 'memory' will be discussed.

The concept of memory “*refers to processes and systems that are responsible for the storage, retention, retrieval and application of information, as soon as the original source of the information is no longer available*” (Weigelt et al., 2023; p. 57). Probably everyone can relive the following situations: There is information that is perceived in a situation but forgotten just a few moments later (e.g., a song on the radio, or the color of a car passing by), then there is information that can be remembered and recalled again and again (e.g., the date of birth or the home address), and further, there is information that is only processed when it is consciously perceived (e.g., the sound of a church tower clock, or the sound of a train in the distance) (Jäncke, 2013). As far back as 1890, William James had distinguished between a primary and secondary memory system. Observations of the patient H.M., who, after undergoing brain surgery, could perceive new information normally but was not able to remember it about 30 – 40 seconds later, though he could still retrieve memories that were stored before the surgery (Scoville & Milner, 1957), support the assumption of different memory systems (e.g., Milner et al., 1998). Accordingly, Milner (1972) assumed a distinction between two overlapping processes: a primary memory process which, however, quickly expires and a secondary process for storing the information in a long-term memory. Later, it was assumed to be more appropriate to differentiate between activated memory and structured memory (Cowan, 1998, cf., Rösler, 2011). The structured memory includes all permanently stored memories, the activated memory describes contents that are currently accessed (Rösler, 2011). Today, three memory systems are usually distinguished: the sensory memory, the working memory, and the long-term memory (e.g., Rösler, 2011; Weigelt et al., 2023). However, before describing different types of memory systems in more detail, the focus should be on distinct memory processes.

The literature refers to different memory processes (cf., Jäncke, 2013; Weigelt et al., 2023): (1) *Encoding*, which refers to the perception of a new stimulus and the storage of the corresponding information by the distinct sensory subsystems (sensory memory). However, the information is only maintained there for as long as the stimulus is present. (2) When the stimulus is no longer perceptible, the corresponding information must be actively retained in the working memory. This process of *retention* requires attentional capacities. (3) If the information that was actively remembered should be retained for a longer period of the time, it must be transferred to a permanent store (long-term memory), this process is called *consolidation*. (4) In order to be able to work actively with the stored information, it must be consciously recalled and be available for the working memory. This process is called *retrieval*. (5) However, it can also happen that information that was once learned is no longer available, this is called *forgetting*. These processes take place in the interaction of the different memory systems, which are described in more detail as follows.

It is assumed that all incoming information about the environment and about one's own body (via various receptors of the sensory systems) are stored in the sensory (or iconic) memory, where they are transformed into sensory impressions (e.g., Thompson, 2012; Weigelt et al., 2023). Research in this field came from Sperling (1960) with respect to the visual sensory memory, and from Darwin et al. (1972) with respect to the auditory sensory memory. Although the storage capacity seems to be relatively large, the storage duration is very short, only up to a few seconds (e.g., Weigelt et al., 2023). The sensory memory can be seen as transient memory. The information collected there is filtered, so that parts are transferred to other memory systems (like the working memory or the long-term memory), while others are deleted (forgotten) (e.g., Thompson, 2012, Weigelt et al., 2023).

In most cases, the information from the sensory memory that has not been erased is transferred to the working memory (e.g., Thompson, 2012, Weigelt et al., 2023). Initially, Richard C. Atkinson and Richard M. Shiffrin (1968) distinguished between a short-term memory and a long-term memory, with the short-term memory as a kind of intermediate memory (Weigelt et al., 2023). However, it can be assumed that this memory system is more than just an intermediate store, so it is commonly referred to as working memory, which is assigned to the executive functions (Jäncke, 2013; Weigelt et al., 2023).[3] Incoming information is not only stored, but it can be actively transferred (Weigelt et al., 2023). The working memory can be characterized by the terms 'maintenance' and 'manipulation' (Jäncke, 2013). Different

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[3] Executive functions are defined as cognitive control processes that enable optimal adaptation of one's own behavior to the situational and environmental circumstances (Jäncke, 2013).

models of the working memory are discussed. Among them, the *three-component model* according to Baddeley and Hitch (1974), the *embedded processes model* proposed by Cowan (1999), and a *facet model* according to Oberauer (2009) (cf., Jäncke, 2013; Weigelt et al., 2023). The *three-component model* assumes three kinds of storage for different kinds of information but limited in capacity (“*the phonological loop for storing and transforming auditory verbal information, the visuospatial sketchpad for visual and spatial information, the episodic buffer as a multimodal storage*” [Weigelt et al., 2023; pp. 59-61]), and a central control system (Baddeley, 2000; Baddeley & Hitch, 1974). Each storage system interacts with the different representations in the long-term memory. The central executive as a superior control system allocates attentional resources to the different memory systems (cf., Jäncke, 2013; Weigelt et al., 2023).

In contrast to the model of Baddeley and Hitch, which clearly differentiates between representations of the working memory and those of the long-term memory, the *embedded processes model* proposed by Nelson Cowan (1999) postulates a close interaction of both memory systems (working memory and long-term memory). This model assumes different levels of the working memory. The representations of the working memory consist of activated representations of the long-term memory on the first level. The number of activatable representations is not limited. On the second level, it is postulated that distinct information can also be activated by focused attention. Here, the capacity of the working memory depends on the limitation of the attentional focus of four items. This model also assumes a central executive for the allocation of attentional resources (cf., Jäncke, 2013, Weigelt et al., 2023).

A more recent model with a more precise understanding of the structure and the function of the working memory was postulated by Klaus Oberauer (2009). His *facet model* differentiates between a declarative and a procedural working memory. The declarative element makes the representation available and can, therefore, be seen as the ‘memory’ part, while the procedural element processes the information as the ‘working’ part. The declarative working memory consists of three levels: (1) The activated long-term memory, which allows selective access to representations stored in the long-term memory. (2) The direct-access region, as a mechanism to build and hold associations between contents and contexts. (3) The focus of attention is responsible for the selection of targets to manipulate. The levels of the procedural working memory are equally built up to the declarative working memory. The representations here are procedures, which can be defined as cognitive or motor actions, and refer to conditions to which they can be applied to or to action outcomes (cf., Jäncke, 2013).

The memory where information is stored over a longer period and without limitations in capacity (i.e., permanent) is the long-term memory (e.g., Thompson, 2012; Weigelt et al., 2023). The long-term memory can be seen as a permanent storage system from which the information can be recalled to the working memory, as needed (e.g., Olivier et al., 2013; Thompson, 2012). With respect to the long-term memory, there are different kinds of stored information. An important aspect in this context is the differentiation between verbal and non-verbal memory (Paivio, 1986), and between declarative and non-declarative memory (Squire, 1987) (cf., Jäncke, 2013). Verbal information refers to knowledge that is linguistically coded and can be expressed in words; non-verbal information refers to knowledge, which cannot, or only to a limited extent, be reproduced in words (e.g., visual impressions) (Jäncke, 2013). Declarative (explicit) information refers to verbal as well as to non-verbal information that can consciously be recalled, while non-declarative (implicit) information refers to knowledge that cannot consciously be recalled (Jäncke, 2013; Thompson, 2012; Weigelt et al., 2023). The declarative memory comprises the episodic memory and the semantic memory (Tulving, 1985), in addition, the autobiographic memory is discussed as an exceptional part (Jäncke, 2013). The episodic memory is time-related and contains knowledge about one's own experiences, e.g., the order of certain events of a day that were experienced (cf., see Jäncke, 2013; Thomson, 2012; Weigelt et al., 2023). The semantic memory is not time-related (one does not know at which time the knowledge was acquired) and contains general knowledge about the world, e.g., lexical, and encyclopedic knowledge, grammatical or mathematical rules (cf., Jäncke, 2013; Thompson, 2012; Weigelt et al., 2023). A dissociation of these two memory systems (episodic and semantic memory) can be proven in patients with lesions in mesiotemporal brain areas (Jäncke, 2013) such as for the example of patient K.C., who lost almost all his episodic memory but was able to use his semantic memory and was further able to store new semantic information (Rosenbaum et al., 2005). The autobiographic memory stores experiences and episodes that are related to one`s own biography and is assumed to serve a more social and self-defining function (for a review, see Fivush, 2011).

Early on, it could be observed that amnesic patients showed normal levels of performance in several tasks without conscious knowledge about these tasks, for example in motor skill learning (Milner et al., 1968) or with the completion of fragmented words and pictures (Warrington & Weiskranz, 1974) (for a review, see Schacter et al., 1993). Non-declarative (implicit) memory refers to knowledge that cannot consciously be accessed (e.g, Thompson, 2012; Weigelt et al., 2023) and is reflected in different manifestations (Schacter et al., 1993): associations, non-associative learning, perceptual priming, procedural memory (cf., Jäncke, 2013; Thompson, 2012; Weigelt et al., 2023). Associative learning refers to the binding of events, which occur simultaneously, e.g., in classical conditioning (as described in Chapter 2.2.1). Non-associative learning refers to habituation, in which a weakening reaction to a stimulus is caused by several repetitions, and to sensitization, in which a reaction to a stimulus is intensified (cf., Thompson, 2012; Weigelt et al., 2023). With respect to motor skill learning and the performance of motor skills, perceptual priming and the procedural memory are assumed to be important (Weigelt et al., 2023). Priming refers to a facilitated processing of a target (probe) stimulus due to a prior stimulus (prime) (Jäncke, 2013). In perceptual priming, the external information received via the sensory systems are processed without involving declarative memory systems (Weigelt et al., 2023). There are many studies that have shown that human behavior is influenced by these unconsciously perceived stimuli (for a review, see Schacter et al., 1993). Related to motor skill performance, the study of Masters and colleagues (2007) has demonstrated that even small deviations from the central position of a goalkeeper in penalty kicks in soccer affects the shot direction of the shooter (cf., Weigelt et al., 2023).

The procedural memory is the storage of automated skills and behavioral routines that can be performed without conscious awareness (cf., Jäncke, 2013; Thompson, 2012; Weigelt et al., 2023). In this context, it was assumed that motor skills cannot be referred to as procedural knowledge *per se* (Maresch et al., 2021). There might be parts that are procedural and cannot be described (e.g., keeping one's balance on a bike), while others are declarative and can be described verbally (e.g., pedaling the bike or pulling the brakes) (ibid.). Furthermore, knowledge about motor skills appears to be both implicit and explicit, depending on how attentional resources are allocated (ibid.). There are situations in which the focus is on the movement goal, and others in which the focus is rather on the performance of the movement. For example:

When reaching for a cup, the focus is more on the position and localization of the cup than on the movements that are necessary to grasp the cup (like extension of the arm, the opening of the hand or the positioning of the hand on the cup). In this case, the agent is not aware of the movements and the performance is rather implicit. This changes as soon as you *hold a cup filled with hot tea in your hands and must transport it to the table. In this situation, the agent will probably be aware of every single movement to keep the cup as still as possible until it is safely put down.*

Motor learning, therefore, might also depend on implicit and explicit processes. Krakauer and colleagues (2019) argue that the characteristics of implicit motor performance (i.e., being executed without awareness) correspond to an overlearned motor skill but should not be generalized for the process of motor learning. Even if extensive practice results in the ability that a motor skill can be executed without awareness, the process of learning that skill might be accompanied by a certain amount of cognitive effort and explicit processes (ibid.).

To end this section, it should be mentioned that the storage of new knowledge in the long-term memory can be either intentional or incidental (cf., Jäncke, 2013, Weigelt et al., 2023). Intentional knowledge is based on explicit processes and is memorized voluntarily. What is to be learned is usually externally prescribed, e.g., learning a specific kata in martial arts like judo or karate, or learning a choreography in dance created by a choreographer. Incidental knowledge is based on implicit processes and is stored without voluntary intention. The learning content is not externally defined, but emerges depending on the situation, e.g., while playing street soccer. It is assumed that incidental knowledge represents the largest part of the memory content (Jäncke, 2013).

2.2.3 Representations of Motor Skills

Now that different memory systems have been introduced, in the following paragraphs, the focus will be on concepts that deal with the question on how motor skills are represented in the brain.[4] For the successful performance of a motor skill, the corresponding knowledge (action representation) and the execution (movement control) is important (Weigelt et al., 2023). Motor skills are executed to achieve a predefined action goal that is commonly a distal effect in the environment (ibid.), e.g., shooting the ball into a goal in soccer. The outcome of an action, measured by its sensory effects in the environment, is associated to that action bidirectionally (ibid.). This interaction of an action and its outcome is described in the *Ideomotor hypothesis* (a summary of the historical beginnings and developments is given by

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[4] Representations of motor skills refer to the cognitive units that are needed for the controlled execution of that motor skill (Weigelt et al., 2023).

Stock & Stock, 2004). On the one hand, when performing an action, a certain effect in the environment is anticipated, and on the other hand, when perceiving or imagining these sensory effects, the corresponding action is activated (Weigelt et al., 2023). This assumption has been methodically investigated for what is known as 'response-effect compatibility' (e.g., Kunde et al., 2004). In addition to the action itself, in interaction with its corresponding action effects, biomechanical parameters such as one's own body size or muscle strength are also part of the action's representation (Weigelt et al., 2023). In this context, the *Common Coding Theory* (Prinz, 1990) postulates that the perception of an action and the execution of that action are stored in a common representation. This action representation is based on the codes of their features distributed across the brain that relate to the distal events (e.g., sensory action effects) and to proximal events (e.g., muscular commands) (*TEC* according to Hommel et al., 2001 [cf., Hommel & Nattkemper, 2011; Weigelt et al., 2023]).

After this explanation of which information (in terms of motor memory content) is stored, the question arises how this information is organized. Semantic knowledge is stored categorically in the brain using concepts (Hoffmann & Engelkamp, 2013). These concepts are defined based on the common features of objects (e.g., the similar shape of coffee cups), but also on associations and experiences (e.g., the symptoms of a disease), or affordances (e.g., the possibility to sit on a chair)[5] (ibid.). In relation to motor skills, so-called Basic Action Concepts (BACs) have been defined (Schack, 2004), which associate individual parts of an action and arrange them in a functional order to achieve the predefined action goal. The single BACs of an action are set in clusters (e.g., elements of the preparatory phase are more interconnected as compared with their connections with elements of the main phase), which can be visualized by the Structural Dimensional Analysis – Motoric (SDA-M) in dendrograms (Schack, 2004; Schack, 2010). However, these dendrograms are not predefined concepts of a motor skill but can vary in dependence of individual expertise (Bläsing et al., 2009).

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[5] Although there are many definitions of the term 'affordances' (cf., Jamon et al., 2018), here it is simply defined as an action prompted by the character of an object.

2.3 Phases of Motor Learning

As stated above (Chapter 2.1), motor learning is a process that develops over distinct phases.[6] Early studies examining behavioral changes during skill learning were conducted by Bryan and Harter as far back as 1899 (Schmidt & Lee, 2011). These studies were based on the acquisition of telegraphy skills over an extensive practice phase. It was observed that an increase in performance was followed by a period in which little or no improvement occurred (‘plateaus’) before further increases in performance appeared (*Hierarchy of Habits*, Bryan & Harter, 1899). Since then, several models of motor learning that define different numbers of phases have been proposed (cf., Magill & Anderson, 2014; Müller & Blischke, 2009; Schmidt & Lee, 2011), with mostly two (e.g., Adams, 1971; Gentile, 1972) or three phases (e.g., Fitts & Posner, 1967; Anderson, 1982), some even more (e.g., Doyon & Benali, 2005). Next, selected models are explained in more detail.

Ann Gentile (1972) proposed a model based on two phases of motor learning: *The initial stage* followed by *later stages*. In the *initial stage*, the movement pattern is acquired by finding out about regulatory conditions and by distinguishing them from irregular conditions in the environmental context. This is achieved by the exploration of different movement possibilities via trial-and-error. At the end of this stage, a general concept of the motor skill should be acquired, but the performance is still variable and lacks efficiency. The *later stages* designation opens the possibility of several phases. The goal of the *later stages* depends on the type of skill, with closed skills aiming for a fixation of the movement pattern, and open skills aiming for a diversification of the movement pattern in dependence of changing environmental conditions (cf., Magill & Anderson, 2014).

A model based on three phases of motor learning was proposed by Paul Fitts and Michael Posner (1967). In the first stage (the *cognitive stage*), the learner acquires the motor skill with a high investment of cognitive resources. Motor performance in this stage is

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[6] The term ’phase’ refers to a period in the development of something (Cambridge Dictionary, n.d.) or to a “*recurrent stage of any cyclical process*” (APA Dictionary of Psychology, n.d.). The term ‘stage’ is defined as “*a relatively discrete period of time in which functioning is qualitatively different from functioning during other periods*” (APA Dictionary of Psychology, n.d.). However, according to von Glasersfeld and Kelley (1982), a phase refers to an undefined stretch of time in which some kind of change is going on. In contrast, a stage refers to a defined progress in the development of something (von Glasersfeld & Kelley, 1982). To distinguish between early and late developments in the progress of motor learning in general, the term ‘phase’ is used in the current dissertation. The respective phase can include several stages, which in turn are clearly defined in line with several theoretical models.

characterized by numerous and large errors and, moreover, by a lack of consistency from one trial to the next. It is still difficult to find out about effective behavioral changes to achieve an improvement in motor performance. In the second stage (the *associative stage*), the errors become less frequent and smaller, the performance is less variable and more consistent. The learner is more and more able to associate their action to sensory effects in the environment and is, therefore, able to make goal-directed adjustments. This stage is also referred to as the *refining stage* and is achieved after an undefined amount of practice. The last stage (the *autonomous stage*) can only be achieved after much practice, which can take up to several years. The performance of the motor skill is almost automatic without attentional control conditions (cf., Magill & Anderson, 2014).

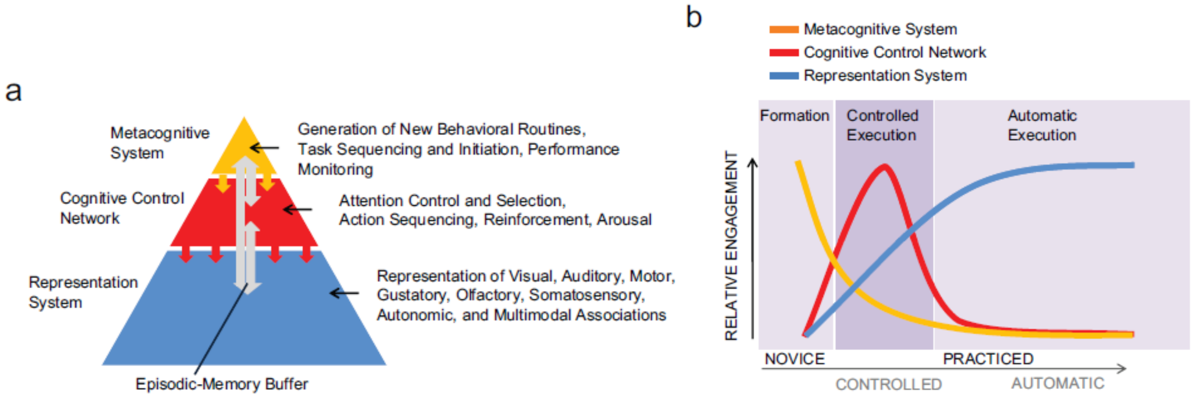
So far, the learning phases have been described rather behaviorally (e.g., with respect to the amount and the magnitude of errors, or the stability of motor performance). In contrast, the model of Julien Doyon and Habib Benali (2005) distinguishes between motor sequence learning and motor adaptation, further, it refers to distinct brain structures. In the early learning phase, a high involvement of attentional processing is proposed; this concerns both motor sequence learning and motor adaptation. Performance improvements develop quickly in this early learning phase. After that, the learning progress slows down and brain regions including the medial temporal lobe (the hippocampus), cerebellar cortices, the striatum, and frontal associative regions become active. After consolidation during further practice, motor cortical regions and parietal cortices remain active with respect to both learning tasks (motor sequence learning, motor adaptation), but the cerebellum is assumed to be dominant for motor adaptation, while the striatum is assumed to be dominant for motor sequence learning. This dissociation of brain structures persists during the process of automatization and retention after a period without further intensive practice. However, the neural basis of motor learning will be explained in more detail in Chapter 2.5.1 of this synopsis, but with an emphasized focus on the brain structures (the cortex, the cerebellum, the basal ganglia) that are important for feedback processing. In the context of motor learning, feedback plays a crucial role for minimizing the discrepancy between the desired movement outcome and the actual performance (cf., Schmidt & Lee, 2011), and will be described in more detail in Chapter 2.4 of this synopsis.

Finally, two models are presented which refer more to the cognitive processes: The *Triarchic Theory of Learning* (Chein & Schneider, 2012), and the model of *Parallel Neural*

Networks (Hikosaka et al., 1999). Based on former research on executive control in combination with recent findings from brain science, Jason M. Chein and Walter Schneider (2012) proposed their *Triarchic Theory of Learning*. This model assumes three distinct cognitive mechanisms (the metacognitive system, the cognitive control network, the representation system) that operate with varying dominance in one of three learning phases (*formation*, *controlled execution*, *automatic execution*) (Figure 1). It is proposed that the interaction of the three systems during the different learning phases enables complex and flexible motor learning. In the early phase of *formation*, the metacognitive system is likely to be dominant to establish new behavior and routines in the first few trials of a new motor task. What follows is a phase of *controlled execution*, in which the acquired movement patterns are repeatedly executed guided by the cognitive control network.[7] In the last phase of *automatic execution*, sensory, motor, and sematic associations are learned under the guidance of the representation system.

Figure 1

Triarchic Theory of Learning by Chein & Schneider (2012, p. 79)



Note: (a) Hierarchical arrangement of the three systems (metacognitive system, cognitive control network, representation system) connected by the episodic buffer. (b) Alternating dominance of the three systems during different phases of learning (*formation*, *controlled execution*, *automatic execution*).

Based on experiments with monkeys using a sequential button-press task, which has to be learned by trial-and-error, Okihide Hikosaka and colleagues (1999) proposed the idea of

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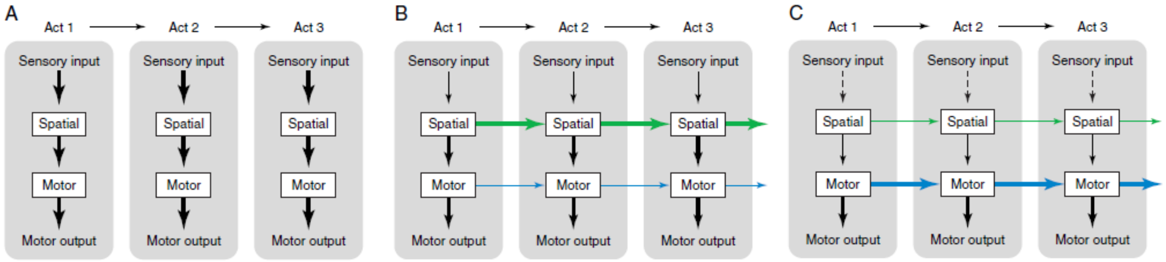
[7] The cognitive control network consists of many separate brain areas (among them, the anterior cingulate cortex [ACC], the pre-supplementary motor area [preSMA], the dorsolateral prefrontal cortex (DLPFC), the dorsal premotor cortex [dPMC], the anterior insular cortex [AIC], the inferior frontal junction [IFJ], and the posterior parietal cortex [PPC]) that often act like a coordinated network (Cole & Schneider, 2007).

two *Parallel Neural Networks* with respect to the automatization of a motor sequence (Figure 2). In this model, a fast-learning system, based on a spatial code, is separated from a slower learning system, based on a motor code. These systems do not operate sequentially but in parallel, though with different emphasis. During the early practice phase, the spatial system which demands attention-dependent processing is the dominant one and teaches the motor system. The connections between the sequences of the motor task are formed very quickly based on spatial codes and in parallel rather slow but steadily based on motor codes. With an increasing amount of practice, the connections based on motor codes become stronger and more stable. In the later practice phase, the motor system now takes over, and as this system requires less cognitive control, the motor sequence is assumed to rely on automatic control.

Figure 2

Model of parallel neural networks by Hikosaka et al. (1999, p. 466)



Note: (A): Pre-learning stage with no connections between the units of a motor sequence (Act 1 – Act 2). (B) and (C): Sequential processes are formed based on spatial (green) and motor (blue) codes. The bolder arrows highlight which process is the leading one in the early (B) versus the late (C) learning phase.

To sum up: Motor learning starts with a first phase of early learning that is characterized by the exploration of several movement possibilities (Gentile, 1972), numerous and large errors, a lack of consistency, weak error detection and correction mechanisms (Fitts & Posner, 1967), and fast performance improvements (Doyon & Benali, 2005). A basic concept or idea of the movement must be developed, which requires the intense involvement of cognitive and verbal processes (Müller & Blischke, 2009). In the following phases, the errors become less frequent and smaller (Fitts & Posner, 1967), and further performance improvements develop over several practice sessions (Doyon & Benali, 2005). The goal of this phase depends on the type of task: With respect to closed skills,[8] the movement is refined and

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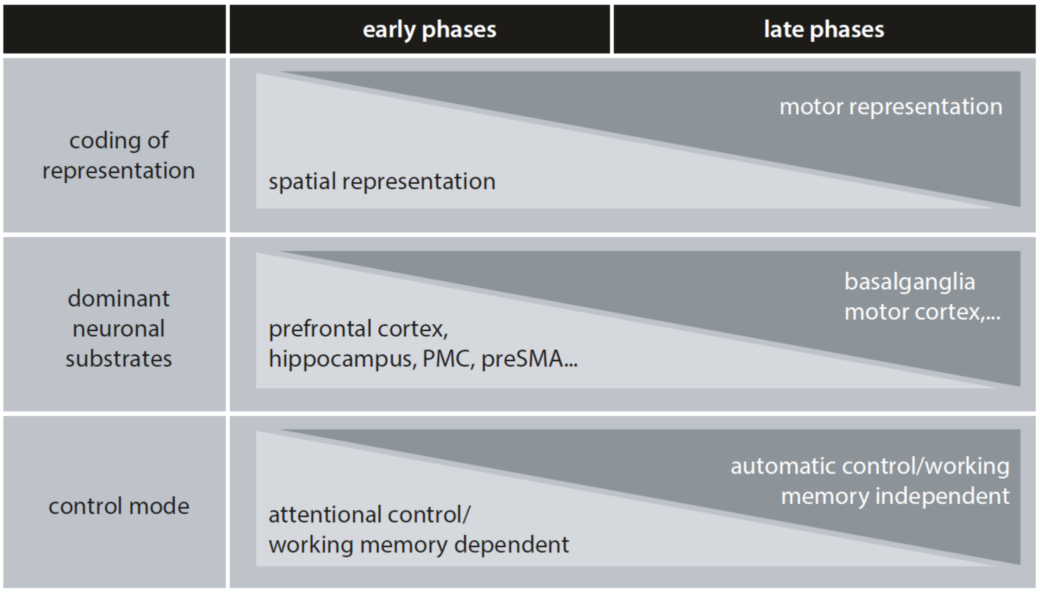
[8] Defined as motor skills that are performed in a predictable and stable environment, e.g., archery (e.g., Schmidt & Lee, 2011).

becomes more consistent. Regarding open skills,[9] there is an improvement in the ability to quickly adapt the movement to changing situations (Gentile, 1972; Müller & Blischke, 2009). In the later phases, the learner can reliably detect and effectively correct errors (Fitts & Posner, 1967). Moreover, some amount of motor automaticity is achieved in which the movement execution demands only minimal attentional resources (Doyon & Benali, 2005).

Figure 3

Early and Late Learning Phases by Weigelt et al. (2023, p. 48)



Note: Changes from early to late phases of motor learning with respect to the representation of motor skills from a spatial code to a motor code (upper row), regarding involved brain areas (middle row), and with related to the control mode from attentional to automatic (lower row).

With respect to the involvement of attentional resources, it should be emphasized that most of the models that were presented above propose a high level of involvement of attentional resources in the early learning phases, which is reduced with further practice, and resulting in a phase in which motor execution underlies processes of automatic control. However, two control modes of human behavior (i.e., execution of motor skills) can be distinguished (Shiffrin & Schneider, 1977): The *controlled processing mode* operates slowly, with demands for attentional resources from the working memory, it only allows serial processing, and is strongly volitional, while the *automatic processing mode* is fast, does not

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[9] Defined as motor skills that must be performed in an unpredictable and constantly changing environment, e.g., team sports like basketball or soccer (e.g., Schmidt & Lee, 2011).

demand attentional resources from the working memory, it allows parallel processing, and is not volitional. Therefore, the automatization of a motor skill (which is important for complex movement control)[10] is strongly characterized by an alternated control mode (Figure 3).

2.4 Motor Learning Based on Feedback Processing

At the beginning of a motor learning process, there is an informational deficit on the learner's part (Olivier et al., 2013). There is yet no basic concept or idea (representation) of the motor skill. There are two possibilities to reduce the lack of information or to support the formation of a motor representation: instruction and feedback (e.g., Olivier et al., 2013; Weigelt et al., 2023). While instructions are directed to the future, feedback is oriented towards the past (ibid.). In the following, the focus will be on feedback. Past-oriented feedback aims to minimize the discrepancy between the desired movement outcome and the actual performance and can be defined as any kind of information before, during, and after movement execution (Reeve et al., 1990; cf., Schmidt & Lee, 2011). In the following section, selected aspects with respect to feedback will be explained, and further be discussed related to motor skill learning. The focus will be on feedback information that is available after the movement execution is completed.

2.4.1 Sources of Feedback Information

In general, there are two sources of feedback information: Self-generated by the learner (i.e., inherent or task-intrinsic feedback), or provided by an external source (i.e., augmented feedback) (e.g., Magill & Anderson, 2014, Schmidt & Lee, 2011). Inherent feedback information is generated by the sensory systems of the learner (e.g., visual, auditive, proprioceptive or tactile) (e.g, Schmidt & Lee, 2011; Weigelt et al., 2023), and can provide a variety of different information about the performance (e.g., Schmidt & Lee, 2011). Inherent feedback can already be perceived during the movement execution (e.g., sometimes it is known that the desired movement goal will not be achieved even before the whole movement is completed) or is generated after the movement execution is completed and the outcome

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[10] The term 'automatization' is defined as "*the development of a skill or habit to a point at which it becomes routine and requires little if any conscious effort or direction*" (APA Dictionary of Psychology, n.d.). The term 'automaticity' is defined as "*the quality of a behavior or mental process that can be carried out rapidly and without effort or explicit intention*" (APA Dictionary of Psychology, n.d.). In the other words, the term 'automatization' refers to the process of developing 'automaticity', which in turn refers to the state in which the execution underlies automatic control processes and requires very few attentional resources, if at all.

can be perceived and evaluated (Schmidt & Lee, 2011). Augmented feedback is generated externally (e.g., by another person, like a coach, but also other external sources, such as video recordings) and can help when internal mechanisms for error detection are not yet well-developed (e.g., in beginners), or when inherent feedback information may not provide reliable information for movement correction (e.g., the movement outcome was not clear for the learner) (e.g., Magill & Anderson, 2014, Schmidt & Lee, 2011). Therefore, augmented feedback is assumed to promote the learning process as it may confirm or correct inherent feedback information (e.g., Magill & Anderson, 2014; Swinnen, 1996). Schmidt and Lee (2011) defined different dimensions of augmented feedback: (1) Augmented feedback can be concurrent (provided during the movement) or terminal (provided after the movement). (2) Augmented feedback can be provided immediately after movement execution is finished or delayed in time. (3) Augmented feedback can be verbal or nonverbal. (4) Augmented feedback can be accumulated (a summary of performance over several trials) or distinct (for each trial). (5) Augmented feedback can provide knowledge of results or knowledge of performance.

If there is inherent feedback generated by the learner itself, why is feedback information from an external source is required? Is augmented feedback necessary for motor practice and motor skill learning? Based on the study of Bilodeau and colleagues (1959), a first assumption was that learning cannot occur without augmented feedback. However, it should be mentioned that in this early study, motor learning was not measured as it is defined in this dissertation (explained in Chapter 2.1), because it lacked a delayed retention test. Later studies could show that augmented feedback does not always affect the performance, which means, improvements in the motor task can occur even when augmented feedback is not given after every trial (e.g., Zelaznik et al., 1978; Magill et al., 1991).

The effectiveness of augmented feedback in motor learning seems to depend on the availability and usefulness of inherent feedback (Schmidt & Lee, 2011). In learning conditions in which inherent feedback provides information that can be used for the performance evaluation and movement correction, augmented feedback is assumed to be redundant for the learning process (Magill & Anderson, 2014). Accordingly, motor learning is also possible without augmented feedback, solely based on inherent feedback information (Swinnen, 1996), which could be confirmed by corresponding research (e.g., Magill et al., 1991; for a review Swinnen, 1996). However, in situations in which inherent feedback information cannot be used effectively, for example, because it is not available based on external conditions (e.g., the learner is not yet able to interpret inherent feedback reliably or a target is not visible) or internal reasons (e.g., the sensory pathways are disturbed due to injury), augmented feedback may be essential for performance improvements and, therefore, for motor skill learning (Magill & Anderson, 2014). Aside from these extremes (redundant versus necessary), there are also situations in which improvements may be possible solely based on inherent feedback information, but in which augmented feedback can help to support and accelerate the learning process (Magill & Anderson, 2014). As stated above, inherent feedback can provide a variety of different data about the performance (Schmidt & Lee, 2011). As attentional resources (defined as the capacity of the working memory to process information; Posner & Boies, 1971) are limited (Abernethy, 2001), the learner might be overwhelmed by the inherent feedback information. In such situations, augmented feedback can support motor skill learning by pointing out the most significant error, especially in complex motor skills with many degrees of freedom (and therefore multiple sources of errors). Therefore, augmented feedback is assumed to supplement the learning process, further, it may lead to rapid improvements in performance, faster than would be the case without such information (Magill & Anderson, 2014). In this context, there is a lot of research proving the efficacy of augmented feedback in the motor learning process (for reviews, see, Petancevski et al., 2022; Lauber & Keller, 2014; Swinnen, 1996).

Another aspect that should be considered is the contribution of feedback (inherent, augmented) to internal mechanisms of error detection. The capability to detect an error to adequately correct it in future behavior is assumed to be crucial for motor skill learning (e.g., Green & Sherwood, 2000), and especially beneficial in later learning phases (Liu & Wrisberg, 1997). Successful error detection is based on a comparison of the desired and the actual produced action, mainly based on sensory prediction errors (e.g., Spampinato & Celnik, 2021). Although augmented feedback is thought to support fast improvements in performance, it is assumed that providing augmented feedback information immediately after movement execution may prevent the development of intrinsic mechanisms for error-detection. Providing immediate augmented feedback information diverts the attention away from inherent feedback information (Liu & Wrisberg, 1997), and may lead to a dependence on this external feedback information (*Guidance Hypothesis*, Salmoni et al., 1984). However, in this context, it could be proven that the delayed presentation of augmented feedback information was beneficial for retention performance (e.g., Swinnen et al., 1990). Delayed augmented feedback information may help to process inherent feedback and, therefore, indirectly supports the development of error-detection capabilities.

The person who provides the augmented feedback information during the practice is confronted with the challenge of limiting the information for the learner to what is necessary to improve performance in a certain situation (Sunaryadi, 2016). There are several aspects concerning the design of augmented feedback. The person providing the augmented feedback must consider how each aspect may affect the learning process. In the following chapter section, the focus will be on the discussion of selected aspects of augmented feedback information.

2.4.2 Augmented Feedback

Augmented feedback is assumed to be a powerful tool to support motor skill learning (Magill & Anderson, 2014; Schmidt & Lee, 2011). There are several moderating factors that affect the influence of augmented feedback on the motor learning process (Magill & Anderson, 2014). Selected aspects will be briefly addressed with respect to their influence on the motor learning process.

Basically, two types of augmented feedback can be distinguished: Augmented feedback can either provide knowledge of results (KR; information as to whether the movement goal was achieved or not) or knowledge of performance (KP; information about how well the movement pattern was executed) (Magill & Anderson, 2014; Schmidt & Lee, 2011). Although KR and KP are assumed to have different effects on motor learning (Brisson & Alain, 1997), both have their justification in application (Magill & Anderson, 2014). KP may be more effective in situations in which a specific movement pattern should be produced (e.g., in dance or gymnastics), while KR is likely to be more efficacious in situations in which a certain effect in the environment should be achieved (e.g., a ball hitting a target) (Brisson & Alain, 1997). In the latter situation, the effect can often be achieved by different movement patterns (e.g., a ball can be thrown at a target and hit it in different ways), so the augmented feedback should not focus on a specific movement pattern (ibid.). However, it is assumed that KR especially may help to apply an external focus of attention (Magill & Anderson, 2014; Wulf et al., 2010). The focus of attention during practice influences motor learning in so far, as an internal focus tends to trigger explicit learning processes, whereas an external focus rather promotes implicit learning processes (Wulf, 2013). According to the *Constraint-Action Hypothesis* (McNevin et al., 2003), an external focus of attention is more beneficial for motor automatization, this is supported by the research (e.g., Shea & Wulf, 1999; Zachry et al., 2005).

Another aspect of augmented feedback concerns the scheduling of augmented feedback during practice. A person providing augmented feedback must decide how often augmented feedback information should be given (feedback frequency) (e.g., Marschall et al., 2007), and when, after movement execution, the augmented feedback information must be provided – immediately or with some delay (feedback delay) (e.g., Travlos & Pratt, 1995; cf., Magill & Anderson, 2014). Although augmented feedback during practice can lead to fast improvements in performance, a high frequency of augmented feedback in practice tends to provoke a dependency on the augmented information as the learner neglects the processing of inherent feedback (*Guidance Hypothesis*; Salmoni et al., 1984), in addition, the augmented feedback information may become a part of the task (*Specificity Hypothesis*; Schmidt, 1991). However, in both cases, the lack of augmented feedback information will provoke a performance breakdown, for example, in test situations without augmented feedback (e.g., Winstein & Schmidt, 1990). With respect to the delay of the augmented feedback, it can be assumed that it may influence the ability to access one’s own mechanisms for error detection. While immediate feedback (without a delay after movement offset) will hamper the development of error-detection capabilities (as the augmented feedback might be the preferred source of feedback), delayed feedback may facilitate the development of error-detection capabilities (*Guidance Hypothesis*; Salmoni et al., 1984). Moreover, it is assumed that longer feedback delays support fast mechanisms based on explicit learning, while in contrast, shorter feedback delays support slow mechanisms based on implicit learning (Hinneberg & Hegele, 2022; Vassiliadis et al., 2022). However, research on feedback delay with respect to motor learning including a consolidation phase (i.e., at least one night of sleep between practice and retention) is scarce and demands further investigation (Travlos & Pratt, 1995).

Further, augmented feedback can either provide a categorical estimation about the performance (qualitative feedback) or more complex information, like numeric performance estimates (quantitative feedback) (e.g., Magill & Anderson, 2014). On the one side, qualitative feedback only provides information if a specific goal has been hit or missed, or if the performance was better or worse as compared to the previous one, without serving more detailed error information. On the other side, quantitative feedback provides more detailed information, such as the direction and magnitude of an error or giving information about different performance measurements, like times, heights or distances achieved. In this context, quantitative feedback is assumed not only to be preferred (Magill & Anderson, 2014) but moreover to be more effective for motor learning (Schmidt & Lee, 2011), which could also be confirmed by several studies (e.g., Bennett & Simmons, 1984; Magill & Wood, 1986; Reeve et al., 1990). However, there are also studies showing that in the early learning phase, learners prefer qualitative feedback even if quantitative feedback information is available (Magill & Wood, 1986). Therefore, it is assumed that qualitative feedback information is more beneficial in the early phases of motor learning (Colino et al., 2020). In this phase of learning, a detailed representation of the movement does not yet exist, and the movement pattern is gradually acquired by trial-and-error (e.g., Gentile, 1972, cf. Chapter 2.3). Therefore, quantitative feedback information will not be suitable at this stage as it may overwhelm the learner. In the later phases of learning, when a good representation of the task is established, quantitative feedback information is assumed to be more efficient when it comes to refining the movement patterns (e.g., Fitts & Posner, 1967, cf. Chapter 2.3).

Likewise, augmented feedback can highlight different aspects of a movement. In this context, it can either refer to errors that were made or highlight the correct aspect of the movement (Magill & Anderson, 2014). In the following, the focus will be on the valence of augmented feedback, which is assumed to have a large impact on the process of motor automatization (e.g., Krause et al., 2018).

2.4.2.1 Valence of Augmented Feedback

As stated above, the valence of augmented feedback information in particular is assumed to have a strong impact on motor skill learning and motor automatization (Krause et al., 2018). The term 'valence'[11] defines the evaluation of an event, an object, or a situation whether it is perceived as negative or as positive (APA Dictionary of Psychology, n.d.). In motor learning based on feedback processing, the valence is either defined by subjective aspiration on one's own performance or by the content provided by the feedback (Weigelt et al., 2023). In the current dissertation, negative feedback refers to correcting feedback and negative aspects of the performance (e.g., if the movement goal has not been reached or focusses on

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[11] The term 'valence' is assumed to be attributed to the field theory following Kurt Lewin (1939).

errors that were made), while positive feedback refers to commendatory feedback and positive aspects of the performance (e.g., if the movement goal has been achieved, or by highlighting correct aspects).

It is believed that error information (negative feedback) is more beneficial for motor skill learning as it provokes behavioral changes, while the primary role of correct information (positive feedback) is rather a motivating one to keep the learner on track (Magill & Anderson, 2014). Nevertheless, it is assumed that positive feedback information rather than negative feedback is more beneficial for motor automatization, as it facilitates dopamine-dependent long-term potentiation (Krause et al., 2018, cf., Chapter 2.5.2 of this dissertation). Moreover, it is argued that the motivating role of positive feedback information has a direct impact on motor learning and, thus, that positive feedback is ultimately more beneficial for motor skill learning (Chiviacowsky & Wulf, 2007). It can be suspected that both valence categories are suitable for performance improvements, however, there are indications that the long-term effects in terms of motor automatization are different. In the *EPAC Hypothesis*, Krause and colleagues (2018) state that the outcome information of negative valence increases attentional processes related to motor planning and motor execution for movement correction. Therefore, practice conditions with a larger amount of negative feedback may lead to a lower degree of motor automatization, as compared to practice conditions serving primarily positive feedback. A similar argumentation came from Maxwell and colleagues (2001), who state that error information forces the learner to form and to prove hypotheses about how to correct the movement (*Explicit-Hypothesis-Testing Hypothesis*), which in turn leads to explicit processing and the learning of verbalizable movement rules, which consequently, hamper implicit learning or motor automatization.

However, especially in the early learning phases, when the performance is not yet stable, almost every trial could result in errors and, thus, in negative feedback. Instead of giving negative feedback for every erroneous trial, in real life it can be observed that the persons that provide feedback only correct very large errors in performance, and reward relatively good performance with positive feedback (Schmidt & Lee, 2011). To find an objective measure of which valence category should be reported back to the learner, a target bandwidth around the desired outcome can be defined. This bandwidth method was established by Sherwood (1988) and has proven to be beneficial for motor learning (e.g., Agethen & Krause, 2016; Badets & Blandin, 2005; Butler et al., 1996).

2.4.2.2 Research on Valence-dependent Augmented Feedback

Related to the question of how the frequency and valence of augmented feedback information affect long-term motor learning in terms of motor automatization, there was a series of experiments using the same experimental setting as the current study (cf. Part I, Chapter 3 of this dissertation). Participants practiced a sequential arm-movement task with subsequent feedback presentation. The movement consisted of three movement reversals. The goal was to hit the reversal points as precisely as possible. The amount of motor automatization was tested using a dual-task paradigm in a pre-test-post-test design with a visuo-spatial n-back task as an additional cognitive task. Krause and colleagues (2018) examined how the frequency of quantitative error information during extensive motor practice affects the degree of motor automatization. Therefore, 42 participants were divided into two intervention groups after the pre-test was conducted. The 100% group received feedback providing quantitative error information (magnitude and direction) to each of the three movement reversals after every trial. The 14% group, on the contrary, received augmented feedback following a fading pattern, whereby the feedback frequency was gradually reduced over the course of practice. As a result, the 14% group received quantitative error information on each of the three reversals only for 14% of all practice trials. With respect to the test-performance on accuracy in the motor task (absolute error)[12] there were no significant differences between the two intervention groups. But the 14% group was able to reduce the dual-task costs[13] for the additive cognitive task to a significantly higher extent as compared to the 100% group. This result shows that a reduced frequency of quantitative error feedback supports motor automatization.

To examine how the valence of augmented feedback during practice affects the degree of motor automatization, Agethen and Krause (2016) implemented a bandwidth for qualitative positive feedback. The test-setting was similar to that described above. 48 participants were split into four groups: Three intervention groups who practiced the criterion task in 760 trials spread over five practice sessions, and one control group without any practice. The BW0-group received 100% quantitative error feedback for each of the three

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[12] Defined as a measure of overall accuracy and calculated as the average absolute deviation between the actual performance and the target performance (Schmidt & Lee, 2011).

[13] Calculated as the difference between single-task performance and dual-task performance and defined as a measurement for the degree of automaticity. Further information can be found in Chapter 3.1.1 of this dissertation.

reversals. The BW10-group received positive feedback in cases when the deviation from the goal-values was below plus or minus 10 degrees. The participants of the BW10-yoked-group[14] received quantitative error information for the same trials as their twin of the BW10-group, regardless of whether their own performance was within the bandwidth. As a result, it could be shown that the BW10-group was able to reduce dual-task costs in the cognitive task significantly more as compared to the BW0-group. A bandwidth for positive feedback induced a stronger amount of motor automatization as compared to high frequent error feedback. That this effect is based on the implementation of a positive feedback valence and not caused by a reduction of quantitative error information (which was also beneficial for motor automatization; Krause et al., 2018) was proven by the BW10-yoked-group. This group was also able to reduce dual-task costs in the retention test, but to a smaller amount as the BW10-group.

The effects of performance evaluation in comparison to the performance of other people (normative feedback or social comparative feedback) has been examined by Zobe and colleagues (2019). A total of 42 participants were divided into three groups: a control group without feedback practice, and two intervention groups in which the valence of the feedback was manipulated in such a way that the performance was either superior when compared to a peer-group (normative-positive group) or inferior when compared to a peer-group (normative-negative group). The results showed dissociative effects with respect to the test-performances. While the normative-positive group was the only group that showed a significant reduction of dual-task costs in the cognitive task (i.e., motor automatization), the normative-negative group was able to significantly decrease the absolute error in the motor task. Normative-positive feedback was assumed to support motor automatization, while normative-negative feedback was assumed to be beneficial for increasing motor precision.

In this context, other studies could also show that normative-positive feedback led to better performance in retention tests. In a sequential timing task (Wulf et al., 2010), participants that have practiced with normative-positive feedback conditions performed significantly better in a transfer test, as compared to participants that have practiced with normative-negative feedback conditions. Even children seem to benefit from normative positive feedback (Avila et al., 2012). Children provided with normative-positive feedback

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[14] A yoked group is a control group in which every participant in this group is assigned to a 'research twin' from the intervention group. The yoked-twin now receives the same treatment as the intervention-twin.

during the practice of a throwing task while wearing opaque swimming goggles have shown better retention performance as compared to children in a control group.

Another aspect with respect to augmented feedback is the question, after which kind of trials augmented feedback should be given. Is it more beneficial to receive augmented feedback after poor performance trials, or after good performance trials? In this context, it could be shown that participants who received augmented KR only after good performance trials showed better retention performance as compared to participants who received augmented KR after poor performance trials (Saemi et al., 2012). Further, the study of Saemi and colleagues (2012) could show that providing KR after good performance trials enhanced self-efficacy.

With respect to error frequency during practice, it could be shown that practice conditions that allow relatively few errors and , consequently, led to many successes, support automatic and implicit motor control, while practice conditions that led to a high number of errors rather provoke cognitive and explicit motor control (e.g., throwing task: Capio et al., 2013; golf-putting task: Maxwell et al., 2001; soccer-kicking task: Savelsbergh et al., 2012). However, in this context, it must be mentioned that instead of manipulating the feedback frequency (as compared to the study of Krause and colleagues [2018], described above), error frequency was manipulated by changing task difficulties. Error-less practice conditions were provided by incrementally raising the task difficulty over the course of practice, while mistake-prone learning conditions were provided by incrementally lowering the task difficulty.

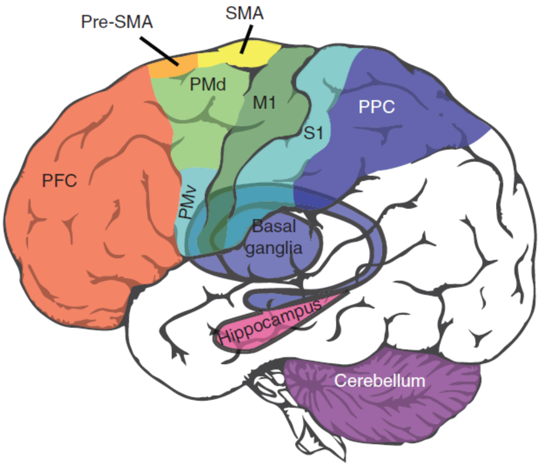
2.5 Neural Basis of Feedback Processing in Motor Learning

2.5.1 Relevant Brain Areas

Certain brain regions turned out to be important for motor learning (e.g., Krakauer et al., 2019) (Figure 4). In the following part, the focus will be on brain regions that are assumed to be relevant for feedback processing in the context of motor learning. First, regions of the cortex are identified that are active during the different learning phases. Afterwards, emphasis will be given to areas of the brain that play an important role for feedback and error processing during the motor learning process (i.e., the cerebellum and the basal ganglia).

Figure 4

Relevant Brain Regions for Motor Learning by Krakauer et al. (2019, p. 613)



Note: Brain regions that are assumed to be important for motor learning: Prefrontal cortex (PFC), pre-supplementary motor area (pre-SMA), supplementary motor area (SMA), dorsal premotor cortex (PMd), ventral premotor cortex (PMv), primary motor cortex (M1), primary somatosensory cortex (S1), posterior parietal cortex (PPC), basal ganglia, hippocampus, cerebellum.

2.5.1.1 Cortex

The (cerebral) cortex is the most differentiated part of the brain and can be divided into four lobes: the frontal cortex, the parietal cortex, the temporal cortex, and the occipital cortex (e.g., Trepel, 2012). Within the cerebral cortex, phylogenetically older parts can be distinguished from younger ones: the allocortex as the older part and the neocortex as the youngest and most highly organized part (ibid.). The allocortex is associated with the limbic system (consisting, among others, of the hippocampus, the amygdala, and the cingulate cortex) (ibid.) and accompanies emotional (e.g., LeDoux, 2000) and memory processes (e.g., Van Strien et al., 2009). The neocortex is associated with brain functions like sensory perception, cognition, language, or the generation of motor commands (e.g., Lodato & Arlotta, 2015).

However, in the initial phases of learning, frontal brain areas are likely to be active. Brain areas relevant for the first acquisition of a new movement pattern are assumed to be the anterior prefrontal cortex, the anterior temporal lobe, the posterior cingulate cortex, and the claustrum (Chein & Schneider, 2012). After the new movement pattern is established and the focus is on a controlled execution of the task, other frontal brain areas – such as the dorsal prefrontal cortex, the ACC, and the pre-SMA – become more relevant (Chein & Schneider, 2012; Halsband & Lange, 2006; Hikosaka et al., 2002). The prefrontal cortex (PFC) is especially attributed to working memory and attentional processing (Halsband & Lange, 2006, Jueptner et al., 1997). The activation of the PFC often goes along with activity of the cingulate cortex (Halsband & Lange, 2006). Within the cingulate cortex, the ACC in particular is discussed with respect to sensory feedback processing (ibid.). Further, the rostral part of the ACC is assumed to be involved in the processing of expectations of action outcomes (ibid.). It could be shown that there was a shift in the activation of this region from external error feedback to internal error detection (Mars et al., 2005). The pre-SMA is assumed to be critical for the acquisition of sequences (Shimizu et al., 2020) and explicit learning (Hikosaka et al., 2002). Other frontal areas that are more likely to be active in early learning phases are the premotor cortex (attributed to spatial processing) and the inferior frontal cortex (known as Broca's area, in the left hemisphere) (Halsband & Lange, 2006).

In the later stages of learning, when movements are assumed to be executed more or less automatically, the activity in the above-mentioned areas is reduced and other brain regions become more relevant. However, brain activity in the later stages is not restricted to a special region but distributed to different areas of the brain (Chein & Schneider, 2012), among them, more parietal areas, like the intraparietal sulcus and the precuneus (Hikosaka et al., 2002), the supplementary motor area (SMA), and the motor cortex (Halsband & Lange, 2006). The activity of the SMA increases with further practice and with implicit learning, and is associated with the storage of sequential movements (ibid.). After an extensive amount of practice, the motor cortex is assumed to be the dominant storage of motor representations and, moreover, is the dominant instance with respect to motor control (Müller & Blischke, 2009).

Beside cortical areas of the brain, there are also noncortical areas that are crucial for motor learning (Shmuelof & Krakauer, 2011). In the following passages, the focus will be on the cerebellum and the basal ganglia, as both structures are associated with learning driven by errors (Hikosaka et al., 2002; Doya, 2000). In the two following sections, these brain regions will be explained and discussed in more detail.

2.5.1.2 Cerebellum

The cerebellum is a brain structure located below the occipital lobe of the cerebrum in the posterior fossa of the skull, dorsal to the brain stem (Trepel, 2012) (cf. Figure 4). With respect to human motor behavior, the cerebellum adopts an important role in motor control with respect to online fine-tuning of movements (Doya, 2000), so lesions of the cerebellum result in deficits in accuracy and coordination (Manto et al., 2012). Imaging studies have shown that the role of the cerebellum extends beyond its role in motor control (Desmond & Fiez, 1998), and is primarily discussed in association with supervised learning (Chapter 2.5.2) (Nicholas et al., 2022; Doya, 2000).[15] However, there is evidence that the cerebellum may also be crucial for reinforcement learning (Chapter 2.5.2) (Nicholas et al., 2022).[16]

From the neurophysiological side, the cerebellum receives afferent information from the pons (whose nuclei transmits information from the cerebral cortex, especially from the frontal lobe), the spinal cord, and the brainstem, and is efferently connected to the thalamus, the nucleus ruber, the nuclei vestibulares, and the formatio reticularis (Trepel, 2012). There is evidence that the cerebellum strongly projects to multiple areas of the PFC in primates (Middleton & Strick, 2001), but also in humans (Buckner et al., 2011). The initial theory about the cerebellar function was proposed by Eccles and colleagues (1967); this was extended and modified by Marr (1968) (Albus, 1971). Independently, the theory of Albus (1971) also arose, which was in line with the ideas stated by Marr in many aspects. Experimental studies on the functional connections within the cerebellum emerged from the work of Ito and colleagues (1982) (Doya, 2000), e.g., based on experiments with rabbits (Ito et al., 1982).

Incoming (afferent) information is based on two kinds of input (Marr, 1968) – a direct way via the climbing fibers (Nicholas et al., 2022, Wolpert et al., 1998), and an indirect way via the mossy fibers (Marr, 1968). The only outgoing (efferent) information is sent by the Purkinje cells that are inhibitory (Marr, 1968; Trepel, 2012, Wolpert et al., 1998). The inferior olive is found to be the only source of climbing fibers (Marr, 1968), and is assumed to represent errors in the motor command (Kawato & Gomi, 1992). However, the direct connections of the climbing fibers (originating from the inferior olive) to the Purkinje cells (of the cerebellum) are

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[15] Defined as learning based on the comparison of the actual outcome with the desired outcome of behavior (Caligiore et al., 2019). More detailed information will follow in Chapter 2.5.2 of this dissertation.

[16] Defined as learning based on rewards and punishment to reinforce a distinct behavior (Caligiore et al., 2019). More detailed information will follow in Chapter 2.5.2 of this dissertation.

assumed to be the basis of online movement control (Marr 1968) and represent the neural substrate of error-driven learning (Ito et al., 1982). There is a controversial discussion about whether the climbing fiber information also provides information about the magnitude and direction of errors (Kawato & Gomi, 1992). While the climbing fibers receive information solely from the olive, the mossy fibers receive information from many different areas or systems of the brain, e.g., from the cerebral cortex via pons, the vestibular system, or the formatio reticularis (Albus, 1971). It is assumed that the mossy fibers are responsible for the learning of the Purkinje cells as a kind of pattern recognition device (Marr, 1968).

With respect to theoretical models, it is assumed that the cerebellum contains internal models of the motor apparatus, which are either forward or inverse models (Wolpert et al., 1998). A forward model would predict the next state based on the current state and the motor command, while an inverse model would provide the motor command to provoke a desired outcome (ibid.). In a forward model, the cerebellum would predict the sensory consequences of an action, the sensory outcome is then compared with the predicted one and based on the sensory prediction error, the motor command is adapted (Krakauer et al., 2019). Grounded on this assumption, the cerebellum is assumed to refine movements based on supervised learning (Nicholas et al., 2022). However, it is noted that biological feedback loops (that allow the comparison between predicted and actual sensory outcomes) are too slow to enable complex movement control (Wolpert et al., 1998). In contrast, in an inverse model, the perceived sensory error would be transformed into a feedback motor command, which in turn would be compared to the original motor command (the *cerebellar feedback-error learning model* [Kawato et al., 1987; Kawato & Gomi, 1992]) (Wolpert et al., 1998). However, rather than arguing whether the internal models of the cerebellum would be either forward or inverse models, it is recommended to maintain the advantages of both models and to assume multiple models within the cerebellum (Wolpert et al., 1998).

In conclusion, the cerebellum is associated with supervised learning based on learning from errors and with externally driven movements (Doya, 2000). Therefore, the cerebellum is assumed to play a crucial role in motor adaptation learning (Doyon & Benali, 2005; Krakauer et al., 2019). However, there is evidence that the climbing fibers also encode expected rewards, so that the Purkinje cells may also code reward-prediction errors which were associated with reinforcement learning (Nicholas et al., 2022). Based on robust bidirectional connections of the cerebellum via the thalamus to, among others, the PFC, a broader role of the cerebellum in human cognition is likely (ibid.). But apart from the learning of motor adaptation, the role of the cerebellum in other motor-learning tasks (like motor sequence learning or motor acuity) is not that clear (Krakauer et al., 2019).

2.5.1.3 Basal Ganglia

The basal ganglia are several subcortical nuclei of the telencephalon (striatum, pallidum, and subthalamic nucleus), which form a neuronal network together with parts of the diencephalon (e.g., thalamus) and the mesencephalon (e.g., substantia nigra) (Trepel, 2012). The basal ganglia receive input from several sources of the brain (including the cerebral cortex) and project this information via the thalamus right back to the cortex (Gigi et al., 2021; Trepel, 2012). It is assumed that the basal ganglia serve to modulate and refine cortical activity through this feedback loop (Gigi et al., 2021).

The striatum, which serves as the main recipient of cortical information (Graybiel, 2000; Trepel, 2012), can be divided into a dorsal and a ventral part (Senatore, 2012). The dorsal part includes the caudate nucleus and the putamen, while the ventral part comprises of the nucleus accumbens (belonging to the reward system [Trepel, 2012]), the septum and the olfactory tubercle (Senatore, 2012). The distinct cell types within the striatum are all inhibitory (ibid.). The globus pallidus (or pallidum) can also be divided into two parts: the external (or lateral) pallidum and the internal (or medial) pallidum (Senatore, 2012; Trepel, 2012). The subthalamic nucleus is the only structure within the basal ganglia which has an excitatory effect (ibid.).

There are different loops within the basal ganglia that modulate cortical activity: a direct pathway, an indirect pathway, and a hyper direct pathway (Senatore, 2012): The striatum receives phasic excitatory cortical input via the direct pathway and projects this to the internal pallidum, whose tonically inhibitory projections to the thalamus are briefly suppressed and which in turn activates cortical activity. Therefore, the direct pathway leads to the disinhibition of certain behavior. The striatum projects in an inhibitory way to the external pallidum via the indirect pathway, which has an inhibitory effect on the subthalamic nucleus, which in turn has excitatory projections to the internal pallidum and, thus, increases its inhibitory effect on the thalamus. The indirect pathway, therefore, is assumed to suppress certain behavior. Further, there is thought to be a hyper-direct pathway via projections from the cortex (especially from motor areas) directly to the subthalamic nucleus, which very quickly leads to disinhibition of all behavior (cf., Senatore, 2012; Trepel, 2012).

However, the direct and the indirect pathway within the basal ganglia are modulated by dopaminergic projections from the substantia nigra (pars compacta) (Senatore, 2012; Trepel, 2012). An increase of the dopaminergic level enhances the activity of the direct pathway (leading to long-term potentiation) and inhibits the indirect pathway (Senatore, 2012). In conclusion, the basal ganglia are based on the different pathways associated with the selection and inhibition of motor commands (Doya, 2000), but are also discussed with respect to a broader role of cognitive functions, like memory and learning (Graybiel, 2000, Trepel, 2012). With respect to motor skill learning, the basal ganglia are crucial for the more cognitive aspects and are discussed with respect to reward-based learning (Krakauer et al., 2019).

Regarding the cerebellum and the basal ganglia, it has been assumed that both these regions are anatomically separated and, consequently, perform a distinct function (Senatore, 2012). Doyon and Benali (2005) have differentiated between two pathways of motor skill learning, one for motor sequence learning and one for motor adaptation. While in an early fast-learning phase of learning, the cognitive processes for both motor sequence learning and motor adaptation are equal and involve the same brain regions. However, in the later slow-learning phase, the consolidation of motor adaptation takes place via cerebellar circuits, while consolidation of motor sequence learning takes place via the basal ganglia (i.e., the striatum). This has been partly supported by the review of Krakauer et al. (2019). Another differentiation between these brain regions can be made with respect to the kind of errors that must be processed during motor learning (e.g., task errors, sensory or reward prediction errors). The cerebellum is assumed to expect the sensory consequences of an action, while the basal ganglia are associated with more cognitive components, such as learning from rewards (e.g., Doya, 2000).

However, there is evidence that parts of the cortex, the cerebellum, and the basal ganglia are activated simultaneously during distinct tasks, which has led to the deduction that there might be direct projections between the cerebellum and the basal ganglia, independent from the cortex (Senatore, 2012). In fact, corresponding links have been found in monkeys (Bostan & Strick, 2010; Hoshi et al., 2005). Based on these findings, it can be assumed that there is a kind of interaction between the cerebellum and the basal ganglia during motor learning, for example, based on a certain kind of error signal (Senatore, 2012).

2.5.2 Basic Neural Learning Mechanisms

With respect to the neural basis of motor learning, general neural learning mechanisms should also be considered. In this context, three neural learning mechanisms are to be distinguished: Unsupervised learning, supervised learning, and reinforcement learning (Doya, 2000; Doya et al., 2001). In the following, these three learning mechanisms will be explained in more detail.

Unsupervised learning can be seen as a kind of statistical learning in which mappings between sensory events and motor actions are built based on the frequency of their co-occurrence (e.g., Caligiore et al., 2019). This kind of learning takes place via Hebbian mechanisms (which goes back to Donald O. Hebb, 1949), in which the synaptic connections of neurons that are often active simultaneously are strengthened, while the synaptic connections without frequent co-activity are weakened (“*cells that fire together, wire together*”, Shatz [1992; p. 64]). Related to motor learning, this implies that a sensory perception that occurs after a certain motor action has been performed is attributed to that very action after several repetitions. Unsupervised learning is assumed to occur primarily in the cerebral cortex (explained in Chapter 2.5.1.1 of this dissertation) (Doya et al., 2001).

Supervised learning is based on a pre-defined output pattern of a particular motor action. Learning occurs via a comparison between the produced and the desired outcome of that action. The difference is computed as error-information and leads to a behavioral change so that, as a result, the acting person learns to produce the desired output pattern with the least amount of discrepancy as possible (e.g., Caligiore et al., 2019). To be able to pre-define a desired movement pattern, a certain idea of the movement must already exist. Supervised learning, therefore, can be seen as kind of model-based learning (Doya et al., 2001). The critical brain region for supervised learning is thought to be the cerebellum (explained in Chapter 2.5.1.2 of this dissertation) (ibid.). However, the error-signal is assumed to be encoded in the climbing fibers of the cerebellum receiving information from the olive, while information about the object to be modelled (a motor command and its sensory output) is provided via cortico-cerebellar connections to the mossy fibers of the cerebellum (ibid.). The Purkinje cells, as the only output neurons, receive incoming information from the mossy as well as from the climbing fibers. Incoming information will be checked against each other. If the motor plan does not lead to the desired sensory input, it can be corrected until the produced action results in the desired sensory input. Supervised learning, accordingly, might be related to augmented feedback containing quantitative error information.

Reinforcement learning is based on the reward of a produced action and aims to maximize gains and to minimize losses (e.g., Caligiore et al., 2019). The outcome of an action is, therefore, evaluated with respect to its value. As a result, the acting person learns to produce the action that leads to the highest profit. With respect to motor learning, this means that it is not just the achievement (or non-achievement) of a certain movement goal that triggers the learning effect, but the evaluation of it. Reinforcement learning might, accordingly, be strongly related to feedback valence. And further, not only is reinforcement learning triggered by the objective evaluation of an outcome of a produced action, but also by the subjective expectation of that objective evaluation. This interaction is described in the *Reward-Prediction-Error Hypothesis of Dopamine* (cf., Glimcher, 2011; Schultz et al., 1997). As soon as an action is executed, the acting person already estimates for themselves whether the performance was good or bad. What follows is the comparison of this expectation with the actual outcome of the action, which can turn out in three ways: First, the result is as expected. In this case, the acting person is able to evaluate their own performance very well, while the value of this evaluation is rather neutral. Second, the result is better than expected. In this case, a reward-prediction-error (RPE) occurs, but a positive one. Third, the result is worse than expected, this is a negative RPE. The valence of this RPE has a strong impact on subsequent processes, as it affects the firing rate of dopamine neurons in the midbrain. In cases of positive RPEs, the firing rate of the dopamine neurons in the midbrain increases and leads to long-term potentiation of the brain areas, responsible for the positive outcome. In contrast, in cases of negative RPEs, the firing rate of these neurons drops below the basal rate which, in turn, triggers a disinhibition of the ACC discussed with attentional processing. A negative RPE is, therefore, assumed to trigger attentional processes for movement correction (Krause et al., 2018). The critical brain regions for reinforcement learning are assumed to be the basal ganglia (described in more detail in Chapter 2.5.1) as the reward signal is assumed to be encoded in the dopaminergic fibers from the substantia nigra, which in turn project to the striatum (as a part of the basal ganglia) and, further, via the thalamus to the cerebral cortex (Doya et al., 2001).

Accordingly, the structures most relevant for learning from augmented feedback are the cerebellum (supervised learning) and the basal ganglia (reinforcement learning), while the cerebral cortex might be rather important for learning from intrinsic feedback information (unsupervised learning) (Doya, 1999; Doya et al., 2001). However, it cannot be assumed that these systems work independently of each other. Instead, an interaction of the neural learning mechanisms can be suspected (Caligiore et al., 2019; Doya, 2000). A theory of how such an interaction between these neural mechanisms could work is described by Caligiore and colleagues (2019) in the *Super-Learning Hypothesis*, which strives to integrate mechanisms of unsupervised learning, supervised learning, and reinforcement learning to enable the acquisition of flexible motor behavior. The authors postulate cooperative connections between the learning mechanisms and the related neural substrates. The extent to which each of these learning mechanisms contributes to the learning of the motor task at a given time might depend on the task itself and the learning condition (e.g., the feedback design).

2.5.3 Neural Correlates of Feedback-based Motor Learning

There are several neural correlates associated with feedback processing (for a review, see Glazer et al., 2018). Neural correlates of feedback processing are divided into those that are related to anticipation (e.g., the cue-N2, the cue-P3, the readiness potential [RP], the contingent-negative variation [CNV] or the stimulus-preceding negativity [SPN]) and those that are related to the outcome (e.g., the FRN, the reward positivity [rewP], the feedback P300 [FB-P3], or the late-positive potential [FB-LPP] (ibid.). In the following, the focus will be on neural correlates that are associated with the outcome, that is, the evaluation of augmented feedback.

2.5.3.1 Event-related Potentials

There are several event-related potentials (ERPs) that are linked with the outcome of augmented feedback (Glazer et al., 2018). It is assumed that the processing of augmented feedback information occurs in three different steps, divided into a first reaction to the feedback, an update of the working memory, and an extended processing of information contained in the feedback (ibid.). There are three ERPs that can be measured in quick succession and that are associated with the different processes mentioned above: The FRN, the P300, and the LFCP. These components are now described in more detail.

The feedback-related negativity (FRN)

The FRN is a component occurring about 250 ms after feedback onset that is strongest at frontal-central electrode sites (Krigolson, 2018; Miltner et al., 1997; for a review, see San Martin, 2012). The dorsal ACC, belonging to the cognitive control network (e.g., Jueptner et al., 1997; Lohse et al., 2014), is assumed to be the generator of the FRN (Bellebaum & Daum, 2008; Hauser et al., 2014). It is claimed that the FRN is an indicator of prediction errors (Holroyd & Coles, 2002), that is, the FRN should be sensitive to the difference between an expected and the actual outcome, independent of the feedback valence (Alexander & Brown, 2011). An outcome worse than expected would be a negative RPE, while an outcome better than expected would be positive one. However, findings reveal that FRN-amplitudes are in most cases more negative after negative feedback as compared to positive feedback (for reviews, see Glazer et al., 2018; San Martin, 2012). Also, the results of a meta-analysis by Sambrook and Goslin (2015) could not support the theory that the FRN is an unsigned prediction error.

According to the *Reward-Prediction-Error Hypothesis of Dopamine* (cf., Glimcher, 2011; Schultz et al., 1997), outcomes worse than expected lead to a disinhibition of the ACC, as the firing-rate of midbrain dopaminergic neurons drops below the basal rate. Since the ACC is associated with the cognitive control network (Jueptner et al., 1997), it is deduced that negative prediction errors provoke increased attentional control for behavioral corrections and adaptations. On the contrary, an outcome better than expected causes increased firing-rates of dopaminergic midbrain neurons, what is assumed to result in long-term potentiation and learning. Based on this theory, it could be predicted that the FRN is more an indicator of negative predictions errors than of unsigned predictions errors.

In this context, it should be mentioned that there is a debate in the scientific community as to whether the FRN is really a negativity or a positivity (e.g., Krigolson, 2018; Proudfit, 2015). It is assumed that a negative component in the time-window of the N200 is the baseline response to feedback, and that this negative response is attenuated by rewards (for a review, see Proudfit, 2015). Although the designation rewP has now become widely accepted for the component, in this work, the original designation FRN is used. This is because both designations can still be found in current studies, especially in the motor domain (e.g., Faßbender et al., 2023; Maurer et al., 2021). However, one could further argue that the designation ’rewP’ already implies some kind of interpretation, while the designation ‘FRN’ first of all states that the component is manifested by a negative deflection and does not preclude an interpretation. Related to the interpretation of the component, there is research suggesting two overlapping processes in the time window of the FRN/rewP (e.g., Höltje & Mecklinger, 2020; Peterburs et al., 2016). In this regard, the valence-dependent difference wave is assumed to be the reflection of the rewP, while the valence-specific waveforms may be linked with prediction errors. In the following, this assumption is adopted. The term ‘rewP’, therefore, always refers to the difference wave, the term ‘FRN’ is associated with conditional waveforms.

Related to the state of research, most studies on the FRN/rewP can be found within the field of the cognitive domain (for a review: Sambrook & Goslin, 2015). However, there is a growing number of studies on the motor domain (Faßbender et al., 2023). Although it is assumed that the FRN might reflect negative as well as positive predictions errors (Alexander & Brown, 2011), the results with respect to the valence-dependent response are relatively homogeneous across studies, with more negative amplitudes after negative feedback (for reviews, see Glazer et al., 2018; San Martin, 2012). Related to practice-related changes, studies in the cognitive domain revealed a practice-induced decrease of the rewP (Walsh & Anderson, 2012). With respect to the motor domain, studies that include more than one session are a desideratum (cf., Margraf et al., 2022a, Part II, Chapter I of this dissertation). As both components (FRN, rewP) correlate with the processing of augmented feedback, it can be assumed that its expression might be predictive of subsequent behavioral changes. However, the results are contradictory, the feedback complexity seems to be a moderating factor on the predictive value of the FRN- and rewP-component for behavioral adaptations (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation). As the FRN is assumed to have its origin in the dorsal ACC, the component was associated with higher attention-dependent processing (Krause et al., 2020). Therefore, higher amplitudes of the FRN might be predictive of lower amounts of motor automatization. In this context, research including a consolidation phase (i.e., one night of sleep, e.g., Erlacher et al., 2012) between practice sessions and retention, and studies based on an extensive practice phase to enable motor automatization are another desideratum in the motor domain (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation).

The feedback-P300

The P300 manifests as a positive deflection and is assumed to have multiple generators (Linden, 2005); it was first described by Sutton and colleagues (1965). There are several ERP-components that may arise in the time window of the P300 (Luck, 2014). A major distinction is made between the earlier P3a and the later P3b (Squires et al., 1975). The P3a, also called the novelty P300, is maximal above frontal electrode sites, while the P3b is maximal above parietal electrode sites (Luck, 2014, Polich, 2003). Both components are sensitive to unpredictable and infrequent stimuli, but the P3b is only apparent if these stimuli are task-relevant (Luck, 2014). The P3b peaks around 300 to 600 ms over parietal areas after stimulus onset and is of greater interest with respect to feedback processing (for reviews, see Glazer et al., 2018; San Martin, 2012). Therefore, the focus here is solely on this later P3b component. In the following, the term P300 is used but it refers to the P3b component as response to augmented feedback.

Although the P300 is one of the most studied ERP-components (for a review, see Polich, 2012) and much is known about the effects of several manipulations (e.g., task difficulty, probability) on the amplitude and latency, there is still no consensus about the cognitive processes reflected by the P300 (e.g., Luck, 2014). With respect to the functional significance of the P300 component, a widely used approach is the context-updating hypothesis (Donchin & Coles, 1988). Adopting this approach to feedback processing in motor learning, the P300 can be interpreted as an indicator of the updating of the internal representation of the motor task (cf., Margraf et al., 2022b, Part II, Chapter I of this dissertation). Although the approach of context-updating is widely used, there is also the interpretation of the P300 as an indicator of a categorization process (Rac-Lubashevsky & Kessler, 2019). As such, Rac-Lubashevsky and Kessler (2019) have tested different interpretations (working memory updating, categorization, and global infrequency). They could show that the P300 is only modulated by the categorization process. Based on their results, they assume that the P300 is an indicator of the working-memory-guided target-identification process. In the current work, the P300 is interpreted as an indicator of working-memory updating (cf., Margraf et al., 2022a, 2022b, Part II, Chapters I & II of this dissertation), however, other possible interpretations (e.g., categorization) should not be excluded when viewed retrospectively.

With respect to feedback processing, the research suggests a valence-dependency on the P300, but the results are inconsistent in the cognitive domain (for a review, see San Martin, 2012). However, there is evidence that the P300 is more positive after positive feedback with respect to motor tasks (Krause et al., 2020). Results in the context of practice-related changes are also inconsistent. While in the cognitive domain, a decrease is reported (e.g., Luque et al., 2012), in the motor domain, an increase was found (Krause et al., 2020) (cf. Margraf et al., 2022a, Part II, Chapter I of this dissertation). Based on the context-updating hypothesis, it is assumed that the P300 might be an indicator of which feedback information is more suitable for the updating of the internal representation of the task at hand (e.g., a motor task). The P300-amplitude after positive feedback might predict behavioral stabilization. Again, the results are ambiguous, and it seems likely that there are some factors (e.g., the goal of the task) that modulate the predictive value of the P300-component (cf. Margraf et al., 2022b, Part II, Chapter II of this dissertation). Research scrutinizing the predictive value of the P300 with respect to long-term learning (retention performance, automatization) is lacking (ibid.).

The late fronto-central positivity (LFCP)

About 450 to 550 ms after feedback onset, a positive deflection over frontal electrode sites can be observed: The LFCP (e.g., Cockburn & Holroyd, 2018). To date, relatively little has been reported about this component as compared to the other components associated with feedback processing (the FRN, P300). The LFCP is thought to be related to supervised learning (Cockburn & Holroyd, 2018; Krause et al., 2020), with cerebellar cortical networks involved in complex feedback processing (the integration of the difference between the actual and the desired output) (Caligiore et al., 2019).

Studies that examined the LFCP report a valence-dependency with more positive amplitudes after negative feedback (e.g., Arbel et al., 2013; Cockburn & Holroyd, 2018; Krause et al., 2020). However, studies examining practice-related changes are lacking (cf., Margraf et al., 2022a, Part II, Chapter I of this dissertation). As the LFCP is associated with supervised learning processes, it can be assumed that the LFCP may be predictive of subsequent behavioral changes, based on the discrepancy between the desired and the current output. Again, research is rare, but the studies homogeneously found a predictive value of LFPC-amplitudes and behavioral adaptations (ibid.). Further, it can be proposed that supervised learning mechanisms rely to some extent on attention-dependent processes, so there might be a predictive value of the LFCP-amplitudes for long-term learning (retention performance, automatization). But again, research on this issue is scarce (ibid.).

2.5.3.2 Time Frequencies

The human electroencephalogram (EEG) consists of five different frequency-bands that oscillate with different velocities: delta (1 – 3 Hz), theta (4 – 8 Hz), alpha (8 – 12 Hz), beta (15 – 30 Hz), and gamma (> 35 Hz) (e.g., Cohen, 2014). The frequency range can vary, depending on the literature (Cohen, 2014). In this work, the focus will be on frontal theta-band activity that is discussed with respect to feedback processing (e.g., Cavanagh & Frank, 2014, cf. Margraf et al., 2023, Part II, Chapter III of this dissertation). Theta-band activity can be found in different areas of the brain and has been associated with cognitive processes on a higher level (ibid.). Frontal theta-band activity is thought to be generated in the medial frontal cortex and in parts of the ACC (Christie & Tata, 2009; Luu et al., 2003). As frontal theta-band activity is found to be sensitive to events that require behavioral adjustments (e.g., negative feedback, errors, conflicts) (Cavanagh & Frank, 2014; Luft, 2014), it has been understood as a general signal for the need of cognitive control to adjust behavior (Cavanagh & Frank, 2014).

With respect to feedback processing, it has mainly been found that frontal theta-band activity was higher following negative feedback in the cognitive domain (for reviews, see Glazer at al., 2018; Luft, 2014). Further, there is evidence that frontal theta-band activity is predictive for subsequent behavioral adaptations (e.g., Cohen & van Gaal, 2013; Van de Vijver et al., 2011). As frontal theta-band activity is assumed to also originate in parts of the ACC, which is considered to be the generator of the FRN (e.g., Hauser et al., 2014), a correlation between both components can be expected, which could be confirmed in some studies (e.g., Hajihosseini & Holroyd, 2013) (cf. Margraf et al., 2023; Part II, Chapter III of this dissertation). However, research related to practice-related changes and the predictive value of frontal theta-band activity is a desideratum (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation).

3 The Present Dissertation Project

3.1 Some Methodological Considerations

Before describing the project in more detail, some important methodological aspects will be described and discussed. First, the question regarding how the degree of automaticity of a motor task can be measured and evaluated based on behavioral data will be dealt with. Second, the physiological basics of neural measurements will briefly be addressed without the intention to give a comprehensive description of the EEG method.

3.1.1 Measuring Motor Automaticity

As described in Chapter 2.3, the early phases of motor skill learning are characterized by a high demand for attention-dependent, explicit neural processes. In this context, the concept of attention should first be addressed, as many different definitions exist. In the current dissertation, attention is understood as a limited cognitive resource for information processing. Posner and Boies (1971) differentiate this understanding of attention between understanding it as "alertness" and "selective attention". With an extensive amount of motor practice, the demand for attention-dependent processes can be reduced and non-attentional (automatic) control processes become dominant (Krause & Blischke, 2023). This reduction of attention-dependent processing and a higher amount of automatic control (i.e., motor automaticity) is important to enable complex motor control and a stable performance under various conditions (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation).

However, there are different approaches to measure the degree of task-related attentional demands (i.e., cognitive load) and, thus, to deduce the degree of automaticity of a task: (1) Behavioral approaches like dual-task measures. (2) Evaluation of physiological parameters like the heart-rate variability (e.g., Solhjoo et al., 2019) or the pupil diameter (e.g., Eckstein et al., 2017). (3) Neural measures like electroencephalography (EEG) or functional magnetic resonance imaging (fMRI). (4) Introspective measures like self-ratings (e.g., Krieglstein et al., 2023). An overview and discussion in terms of applicability in the motor domain can be found in Krause & Blischke (2023). In the following, the focus will be on behavioral measures, especially the dual-task paradigm.

It is assumed that attentional cognitive resources are limited and, therefore, the ability to execute two or more tasks (which demand the same neural resources) at the same time is limited (Abernethy, 2001), depending on how many capacities the individual task requires. Therefore, dual-task methods are used to either estimate any remaining spare attentional cognitive resources during the performance of a task that implies some degree of cognitive load, or to assess the amount of cognitive effort the performance of a task requires (Fisk et al., 1986). From the concept of motor automaticity, it is assumed that, if the performance of a motor task is mainly guided by processes of automatic control, it is likely to be possible to perform a secondary cognitive task with minimal performance decrements in the motor task. Based on this assumption, the degree of motor automaticity can be estimated using cognitive secondary tasks (Agethen & Krause, 2012; Krause & Blischke, 2023). The dual-task paradigm is based on two tasks: The primary task for which the degree of automaticity (or the need for attentional resources) should be determined, and the secondary task as an additional task as a performance measure (Abernethy, 2001). The degree of automaticity is than assessed based on so-called dual-task costs (DTC), defined as performance differences between single-task and dual-task performance (Krause & Blischke, 2023). The amount of DTC in the secondary task is thought to depend on the degree of automaticity of the primary task.

However, there are several things to consider to properly apply the dual-task paradigm to measure motor automaticity (Abernethy, 2001). The first aspect that should be discussed is the choice of the secondary task. The choice of which secondary task is suitable for assessing the degree of automaticity of the primary task depends on the type of cognitive requirements on which the primary task is based on (Fisk et al., 1986). Wickens (2020) proposed a multiple resource model for attentional demands based on functional task codes which can, for example, be either verbal or spatial (in contrast to the undifferentiated processing capacity model stated by Kahneman [1973]). To reliably determine the degree of automaticity of a motor skill, it must be ensured that the secondary task demands for the same cognitive resources as the primary task. Further, the secondary task must have a stable level of difficulty throughout the tests (Fisk et al., 1986). This means, there should be no possibility for the participants to develop strategies that make it easier to perform the secondary task in later phases of the tests as compared with earlier phases.

A second aspect to discuss concerns a baseline measure. Dual-task measures can only be interpreted if they are evaluated in relation to the single-task performance (Abernethy, 2001). The comparison of the single-task performance and the dual-task performance in the secondary task defines the DTC. If there was a significant difference between dual-task and single-task performance in the additional task, it is assumed that the primary task still requires a lot of attentional resources, and the amount of automaticity is deduced to be low. If there was a high amount of automaticity of the primary task, little or no differences in the single- and the dual-task performance are expected with respect to the secondary task.

A third aspect relates to the task prioritization, which defines the amount of attentional resources allocated by participants to concurrently performed tasks (Abernethy, 2001; Wickens, 2020). Prioritization instructions affect task performance as task performance varies in dependence of the instruction of attention allocation (Wickens, 2020). Since it can be assumed that the attentional resources, especially for novices, are not sufficient for the simultaneous execution of two tasks, prioritization might be given to either one of the tasks or to both tasks. Therefore, prioritization instructions are recommended to ensure a homogeneous test setting. Priority might be instructed for one task, so that performance decrements in dual-task conditions can be measured for the other task. When measuring the degree of automaticity, priority is set on the primary task, so that DTC occur on the secondary task if prioritization was successful. Whether participants have followed the prioritization instruction can be controlled by comparing the single-task and dual-task performance in the primary task. Optimally, there should be no measurable differences in the performance of the single-task and the dual-task condition.

However, besides a higher amount of automatic control related to the primary (motor) task, there are also other aspects that can explain a reduction of DTC in the secondary task (Agethen & Krause, 2012). This will be briefly discussed in the following. A significant reduction of DTC can also be a result of task integration strategies (e.g., effective switching of attention between the two tasks) (Agethen & Krause, 2012; Blischke et al., 2010). It could be shown that several repetitions of the dual-task test setting (i.e., the combination of the primary task with a selected secondary task) result in a reduction of DTC; this is more likely based on an integrated processing of both tasks than the automatization of the primary task (ibid). In the study of Agethen and Krause (2012), participants practiced an arm-movement sequence with three movement reversals (similar to the criterion task used in the current setting, Chapter 3.3) in 460 trials distributed over six practice sessions. At the beginning of each practice session, a dual-task test was conducted consisting of three trials of a cognitive n-back task, three trials of the criterion motor task, six dual-task trials (with prioritization of the cognitive task to promote automatization of the primary task [e.g., Blischke, 2000]), another three trials of the criterion motor task, and three more trials of the cognitive n-back task. The test-structure was ordered in such a way to prevent sequence effects (e.g., Agethen & Krause, 2016). As motor automaticity should be independent from the test-context, a transfer dual-task test based on a Sternberg-task was conducted before the first practice intervention on Session 1 and as a retention test on Session 7. As a result, DTC were reduced from Session 1 to Session 7 in the n-back-task test setting (that was repeated multiple times) but not in the Sternberg-task test setting. Based on these findings, the dual-task test setting should be treated as a pre-post-test (conducted before the first practice and the last practice), and not as a part of every practice session.

However, with respect to the current setting, the same secondary task (n-back) was used in the pre-acquisition test, the pre-test, and the retention test. The study of Agethen and Krause (2016) has proven that the performance of multiple dual-task test blocks is not critical in the current setting, using the same secondary task in a similar setting. It could be shown that a control group without practice intervention was not able to reduce DTC in the retention test. Therefore, the reduction of DTC should be based on the practice intervention and not on multiple dual-task test blocks in a pre-test-post-test design. Further, the interstimulus-interval during the cognitive n-back task was alternated in pseudorandomized order between 700 and 1000 ms (as was also the case in the study of Agethen and Krause [2016]) to further limit the possibility of task-integrated processing.

3.1.2 Selected Aspects of Neural Measurements

The neurons of the brain communicate with each other via chemical and electrical signals (e.g., Gaho et al., 2018). This neural activity can be measured based on different methods (e.g., electroencephalogram [EEG], positron emission tomography [PET], functional magnetic resonance imaging [fMRI]) (e.g., Thompson, 2012). While PET and fMRI are based on measuring regions with increased blood flow, EEG is based on measuring the electrical activity at the surface of the scalp (Luck, 2014). The choice of method depends on the study and its objective. Comparing the advantages and disadvantages of the common methods, the EEG is thought to be the most suitable to investigate movement-related brain activity in high temporal resolution. As compared to the other methods (PET and fMRI), the EEG is relatively inexpensive, non-invasive, and not very uncomfortable for the participants during the recording. However, it should be kept in mind that the spatial resolution is low (Thompson, 2012).

Event-related brain signals measured by an EEG are assumed to reflect electrical activity originating within the brain (Rugg & Coles, 1995). The origin is thought to be the postsynaptic signals (PSPs) following a neurotransmitter after binding to a receptor. A PSP creates a tiny electrical dipole in the single neuron, but too weak to be measurable at the surface (cf., Luck, 2014). Synchronous activity of many neurons is a prerequisite for the neural signal to be measurable at the surface of the head passing through all structures that were between the source and the electrode (e.g., the skull bone). However, the synchronous activity based on the dipoles of many neurons would cancel out if the neurons are oriented in different ways. Therefore, an electrical signal originating in synchronous activity of a larger population of neurons can only be measured if all these neurons are oriented in the same way. This is the case for the pyramidal cells in the cerebral cortex, being vertically aligned to the surface. EEG recordings, therefore, primarily reflect activity of the cerebral cortex (ibid.).

The EEG (first discovered and described by Hans Berger in 1929) in its raw signal of electrical brain activity is not suitable for examining the highly specific cognitive neural processes of the brain (Luck, 2014). The raw signal of the EEG is a mixture of activity from different neural sources. To investigate specific neural processes, brain activity refers to the occurrence of a certain external stimulus (e.g., augmented feedback). To extract the stimulus-specific activity from the spontaneous background activity, the neural response to the stimulus is measured several times (e.g., over many trials). By averaging all trials, the specific response to the stimulus – the event-related potential (ERP) – becomes visible as the irregular background activity averages out. This is called the ERP technique (Luck, 2014). It should be noted that this measurement only reflects neural responses that appear at the same latency and phase over trials, thus, an ERP is time- and phase-locked to the stimulus. However, there is also neural activity that is related to the stimulus but do not match in phase over trials (Tallon-Baudry & Bertrand, 1999), and thus, is time-locked, but not phase-locked to the stimulus. This neural activity can be captured by dividing the signal into its frequencies via time-frequency analysis (Cohen, 2014). In the following, selected aspects of the neural measurements will be discussed. For more information, the works of Steven J. Luck (2014) and

Michael X. Cohen (2014) are highly recommended, which are also the main references for the following methodological considerations.

The EEG is recorded via electrodes on the scalp (Luck, 2014). Although the spatial resolution of an EEG is relatively low, it is important that all electrodes are placed at defined locations of the scalp, and thus, always above the same brain areas. Therefore, a standardized system was developed for the designation and placing of the electrodes on the scalp (*International 10-20 System*, Jasper, 1958). It is recommended to use between 16 and 32 active electrodes (Luck, 2014). Especially, if the region of interest is defined in advance, there is no need to use as many as electrodes as possible. In the current dissertation study, the electrodes that should be evaluated (FCz, Pz) were defined in advance based on previous research (cf., Chapter 2.5.3).

However, anyone working with EEG data must be aware that the recording not only consists of neural brain activity, but also contains signals from non-neural sources (Luck, 2014). These activities that are included in the data and do not have its origin in the neural activity of the brain are called ‘artifacts’ (Savelainen, 2010). Those artifacts may decrease the signal-to-noise ratio[17] of the averaged data, so that possible differences between groups or conditions may not be detected (Luck, 2014). In general, there is a distinction between two major sources of artifacts: First, artifacts that depend on the participant’s body (internal or physiological artifacts), and second, artifacts based on the recording environment (external or artificial artifacts) (Luck, 2014; Savelainen, 2010; Tandle et al., 2015). In the context of measuring movement-related brain potentials (as in this dissertation project), physiological artifacts provoked by movements of the body might be problematic. In the current dissertation project, the experimental setup and especially the placement of the participants was thought out carefully to minimize the risk of muscular artifacts. More details can be found in the description of the current experiment (cf., Chapter 3.3). To sensibilize the participants to the problem of body movements, they can be shown the impact of their body movements before the recording. Blinking of the eyes can hardly be avoided during the entire experiment, therefore, it is important to avoid blinking at the moments of interest (e.g., after the presentation of the criterion stimulus). This fact should be mentioned in passing during the briefing, rather than becoming an additional cognitive task for the participants.

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[17] The signal-to-noise ratio (SNR) is a measurement to evaluate the quality of the EEG data (Cohen, 2014).

As mentioned above, based on the raw EEG-signal, no evaluation of the cognitive neural processes of the brain can be made. The signal must pass through certain processing steps until evaluable data is obtained. A typical pre-processing pipeline from the raw EEG signal to an ERP includes the following steps: filtering, re-referencing, ocular correction, segmentation, baseline correction, artefact rejection, and averaging. However, these steps will not be described further here. The pre-processing pipeline used in this dissertation is based on the recommendations of Luck (2014). For the specific settings used for the analysis, please refer to the cumulus of this dissertation (Chapter I – II), and for more theoretical background, see Luck (2014).

While there are relatively clear guidelines and recommendations regarding the analysis of the data for ERP analysis (e.g., Luck, 2014; Picton et al., 2000; Woodman, 2010), this is not the case for time-frequency analysis. An aspect that should be discussed is the question of whether it is useful or necessary to do a time-frequency analysis when the EEG data is already analyzed based on ERPs. Does a time-frequency analysis really add value to the data or is this analysis rather redundant? Although an ERP analysis provides many advantages (e.g., simple and fast data computation, high temporal precision and accuracy) there are limitations (Cohen, 2014; Luck, 2014). According to Cohen (2014), the main limitation is that there are a lot of processes and dynamics in EEG data that cannot be captured with ERPs. It may, therefore, be very difficult to interpret ERPs, especially null results. However, some processes and dynamics that cannot be depicted by ERPs may be represented by a time-frequency analysis. To be able to represent as many dimensions of the EEG data as possible, it is advisable for a careful analysis to take a look not only at the time-dimension (ERPs) but also at the frequencies that are contained in the EEG signal.

With respect to time-frequency analysis, it is important to define some terms. An EEG signal reflects a mixture of overlapping frequency-bands that occur simultaneously in time. A frequency-band is primarily characterized by its frequency (speed, defined in numbers of cycles in one second given in Hertz, Hz) (Cohen, 2015). Time-frequency analysis refers to the frequencies contained in the EEG signal at a specific time-point. Representations of time-frequencies can either be analyzed with respect to power or with respect to phase (Cohen, 2014). Power refers to the height of amplitude given in micro volt squared, μV^2. Phase refers to the position along its cycle, e.g., ‘peak’ or ‘trough’ (Cohen, 2014 & 2015). In the following, the focus will be on the analysis of power. Analysis of the phase can be found as intertrial phase clustering (ITPC) but this is beyond the scope of this work.

Related to time-frequencies, the terms ‘frequency-band’ and ‘oscillation’ are common and are often used synonymously, which should be taken with caution. Neural oscillations are associated to distinct neurophysiological mechanisms and are characterized by rhythmic activity (Cohen, 2014). A rhythm is defined by regular repetitions, thus, a certain periodicity (Bullock et al., 2003). A periodicity of the frequencies cannot be unequivocally proven by a time-frequency analysis. The results of a time-frequency analysis, therefore, cannot be interpreted as neural oscillations *per se* (Cohen, 2014). As a consequence, the term ‘frequency-band’ is preferred, as it simply describes the results of the analysis, without directly referring to the neurophysiological mechanisms they are based on (ibid.).

Event-related brain activity can be categorized as ‘evoked’ or ‘induced’, the difference being the phase-relationship to the stimulus (Chen et al., 2012; Tallon-Baudry & Betrand, 1999). Evoked activity is time- and phase-locked to the stimulus or the event and, therefore, only detects activity that matches in time and phase (position along the cycle), while induced activity is only time-locked to the stimulus but not phase-locked and, consequently, jitters in latency (Cohen, 2014; Tallon-Baudry & Betrand, 1999). An ERP is detected by an averaging process (Luck, 2014) and is, accordingly, categorized as phase-locked or evoked. Thus, an ERP cannot reflect induced activity that might also be related to the stimulus or the event. Time-frequency analysis can provide information about this induced activity (Cohen, 2014; Herrmann et al., 2014; Tallon-Baudry & Bertrand, 1999). There is evidence that evoked and induced activity reflect different neural processes (e.g., Cohen & Donner, 2013; Hajihosseini & Holroyd, 2013). As induced activity is a self-organized occurrence and is not directly in phase with the stimulus (David et al., 2006), it is often discussed as an indicator of top-down processes (Chen et al., 2012; Tallon-Baudry & Bertrand, 1999). In contrast, evoked activity is considered in relation to bottom-up processes (Chen et al., 2012).

Having clarified some important aspects related to time-frequencies, the focus is now on the method. There are different methods for computing a time-frequency analysis, e.g., the fast Fourier transform (FFT), the short FFT, the Hilbert transform, multitapers, Morlet wavelets, or complex Morlet wavelets (cf., Cohen, 2014). In the following, the focus will be on complex Morlet wavelets, as it is the most common approach for conducting time-frequency analysis (Williams et al., 2021). Morlet wavelets are based on a sine wave that tapers off to zero at both ends (Gaussian function). Moreover, complex Morlet wavelets contain a real and an imaginary part, making them suitable for extracting the power and the phase of a frequency-band. The time-frequency analysis now compares the defined wavelet for one frequency with the EEG signal, this is done for each point in time (continuous wavelet transform). Based on this method, a calculation is made of how strongly the respective frequency-band is represented in the data at different time-points. However, there are some issues with time-frequency analysis that should be considered when analyzing the data: the time-frequency trade-off, the power law (1/f phenomenon), border and smearing effects, and baseline normalization (cf., Cohen, 2014; Leuchs, 2019). More information on the problems and an evaluation related to this dissertation can be found in the appendix of this dissertation.

Although it is assumed that the most appropriate methods and settings were chosen for the time-frequency analysis for the current data set, some kind of standard in data processing should be developed for the time-frequency analysis, as is the case for the analysis of ERPs (e.g., Luck, 2014; Picton et al., 2000; Woodman, 2010). This is also important to be able to compare the results of different studies and to make sure that different results are not a consequence of differences in the processing pipeline of the data.

3.2 Aims of the Current Study

This dissertation aims to provide a first comprehensive picture of the neural correlates related to the processing of valence-dependent augmented feedback in extensive motor learning (cf., Margraf et al., 2022a, 2022b, 2023; Part II, Chapters I – III of this dissertation). Specifically, the first goal was to replicate previous results related to the valence-effects of the ERPs discussed with valence-dependent augmented feedback processing (FRN, P300, LFCP) and to extend these results with respect to practice-related changes. As augmented feedback can support the process of motor learning, a second goal was to examine the predictive value of feedback-related ERPs (FRN, P300, LFCP) with respect to short-term behavioral adaptations (goal-directed[18], goal-independent[19]) and long-term learning (retention performance, motor

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[18] Defined as adequate error correction in subsequent performance, based on a clear assignment of the error information to a specific motor command (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation).

[19] Defined as less directed change of the subsequent performance that will not necessarily correct the error, as the error information cannot be ascribed to a specific motor command (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation).

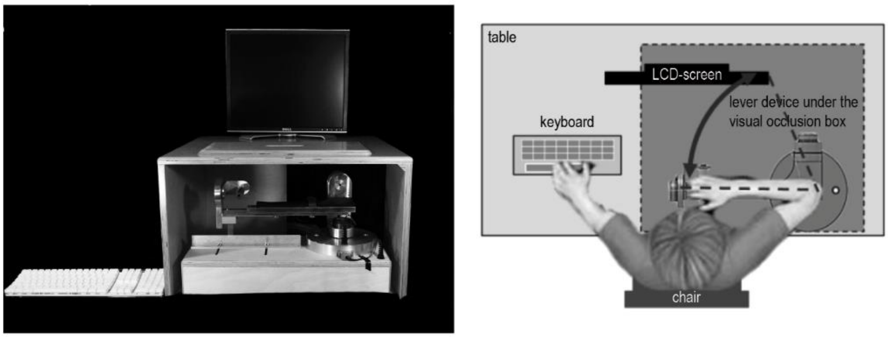
automatization). A third goal was to supplement the ERP results with a time-frequency analysis with a focus on frontal-theta band activity. Based on these extensive analyses, this dissertation aims to contribute to a better understanding of the neural mechanisms involved in feedback-based motor learning. For more details, please refer to the Chapters I – III in the cumulus (Part II) of the present dissertation.

3.3 The Sequence-learning Experiment

In the following, the research experiment is only briefly described, since more details can be found in the cumulus of this dissertation (Margraf et al., 2022a, 2022b, 2023, Part II, Chapters I – III of this dissertation). The participants learned an elbow-extension-flexion movement sequence with three movement reversals executed with the right arm. The movement was performed with an adjustable lever device without the possibility of visual movement control. The goal of the task was to hit the reversals as precisely as possible within a maximum movement time of 1800 ms. The experimental setup is shown in Figure 5 (for more details about the apparatus and the setup, refer to Margraf et al., 2022a, Part II, Chapter I of this dissertation).

Figure 5

Apparatus and Experimental Setup by Margraf et al. (2022a, p. 6)

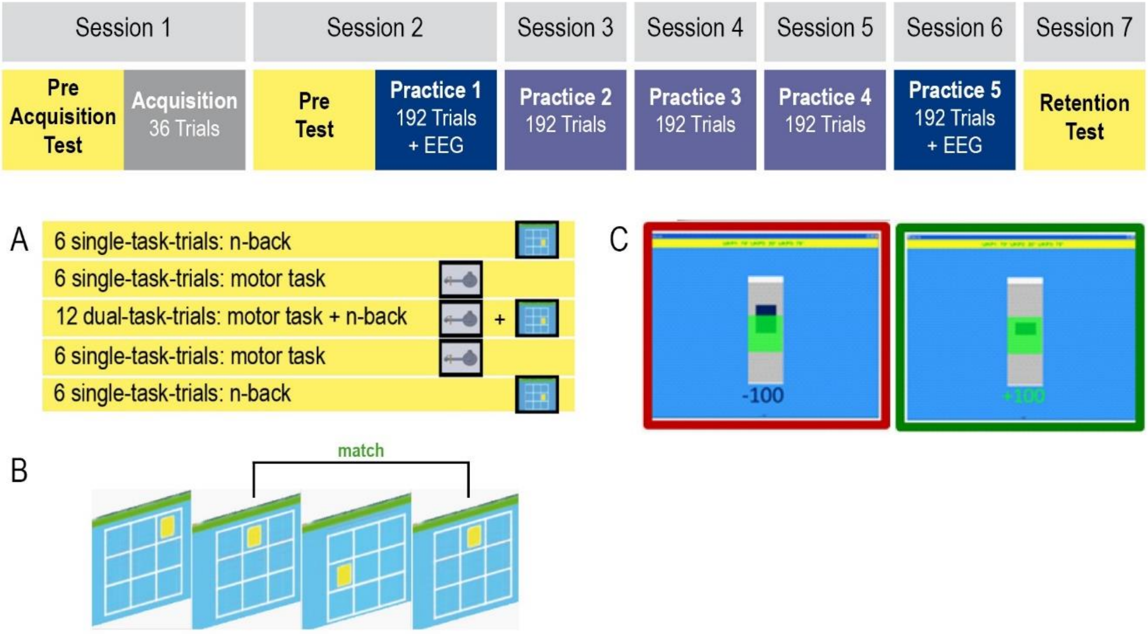


Note: The apparatus is shown on the left side with the arm-lever device placed under a wooden box. The monitor for displaying the instruction slides and feedback presentation is located on the top of the box. A keyboard serves as input device for the participants. The experimental setup is shown on the right side with the participant seated in front of the setup. One arm is place on the lever, while the other is placed on the keyboard.

At this point, only the placement of the participant in front of the experimental setup should be discussed in more detail, since this is important for the avoidance of artifacts during the EEG recording (cf., Chapter 3.1.2). Large body movements and muscle tension can be prevented by ensuring that the participants have a comfortable position during the EEG recording. Therefore, the height and the position of the seat were adjusted in such a way that the participants were able to place the arm in a relaxed position on the lever device, so that no tension in the neck and the shoulder muscles should exist. Further, it was ensured that the participants sat centrally in front of the monitor, so that it could be easily seen without turning the head or lifting the gaze. In addition, the participants had the opportunity to move and, thus, to relax their muscles with regular breaks of self-determined length. Fatigue symptoms were also mitigated by these breaks.

Figure 6

Overview of the Experimental Sessions by Margraf et al. (2023, p.1302)



Note: The top row shows the different experimental sessions. The structure of the dual-task test conducted in Session 1, Session 2, and Session 7 is shown in **A**. An example of a n-back task trial is displayed in **B**. The feedback during the practice phase (Session 2 – Session 6) can be found in **C**.

The experiment comprised a total of seven experimental sessions that had to be completed within 14 days, with at least 24 hours between two subsequent sessions. An overview of the experimental sessions can be found in Figure 6. Five sessions (Session 2 to Session 6) included an extensive practice phase (with 192 trials each), with subsequent feedback presentation after every trial. This augmented feedback was based on a performance-adaptive bandwidth for positive feedback, but only for the reversal with the largest deviation from the goal value. Feedback was given as a bar graph, providing information about the direction and the magnitude of the error, with the bandwidth displayed as a green transparent bar that overlaid the error bar (Figure 6, C). Therefore, on the one hand, the feedback gives qualitative feedback based on the feedback valence (positive: performance within the bandwidth, negative: performance outside of the bandwidth) while, on the other hand, also giving quantitative feedback information based on the error bar (transported with both feedback conditions) (for more information about the feedback design, refer to Margraf et al., 2022a & 2022b; Part II, Chapters I & II of this dissertation). EEG was recorded in Practice 1 (Session 2) and Practice 5 (Session 6).

The degree of motor automatization was tested three times: Before acquisition in Session 1 (pre-acquisition test), before the first practice in Session 2 (pre-test), and in Session 7, which was terminated one day after the completion of the extensive practice phase (retention test). The degree of automatization was tested using a dual-task paradigm with a n-back (2-back) task as an additional cognitive task (Figure 6, B). Both tasks (the n-back task and the criterion motor task) were performed under single-task and dual-task conditions with the prioritization on the motor task in the dual-task condition (Figure 6, A). DTC were calculated for the n-back task as the performance difference between single- and dual-task conditions. Further details about the procedure can be found in the cumulus (Margraf et al., 2022a; Part II, Chapter I [with respect to the acquisition and the extensive practice phase], and Margraf et al., 2022b; Part II, Chapter II [with respect to the dual-task tests]).

3.4 Hypotheses

The following is a brief discussion of the hypotheses. More detailed descriptions can be found in Part II of this dissertation in the corresponding Chapters I – III.

3.4.1 Behavioral Hypotheses

3.4.1.1 Practice-related Effects

In relation to the extensive practice phase, it was expected that performance in the criterion motor task would improve over the course of practice (from Practice 1 in Session 2 to Practice 5 in Session 6). It was anticipated that the performance would most likely become more accurate (reduction of the absolute error), i.e., the participants should be able to hit the movement reversals more precisely in the last practice session as compared with the first practice session. Further, the performance would likely become more consistent (reduction of the variable error), i.e., there should be less variability in the last practice session compared with the first one (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation).

3.4.1.2 Learning-related Effects

With regard to the test-performance (pre-acquisition in Session 1, pre-test in Session 2, retention test in Session 7), it was expected that the performance in the criterion motor task would most likely become more accurate (reduction of the absolute error) and more consistent (reduction of the variable error) in the retention test as compared with the pre-test. With respect to the dual-task condition, participants were told to prioritize the motor task, it was therefore expected that while DTC would likely be evident in the additional cognitive task (n-back) they would not be in the motor task. Further, regarding the additional cognitive task, it was anticipated that DTC would likely be reduced for the retention test as compared with the pre-test (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation).

3.4.2 Neural Hypotheses

3.4.2.1 Valence-dependent Effects

For the time-window from 200 to 300 ms after feedback onset, the rewP (FRN_{diff}) was predicted to be evident with more negative amplitudes of the FRN (FRN_{peak}) after negative feedback as compared with positive feedback (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation). The amplitudes of the P300 in a time window from 300 to 600 ms were expected to be more positive after positive feedback as compared with negative feedback (ibid.). Regarding the LFCP in a time window from 450 to 550 ms, the amplitudes were also expected to be more positive but after negative feedback rather than after positive feedback (ibid.). Pertaining to frontal theta-band activity, it was anticipated that theta power would likely be higher after negative feedback as compared with positive feedback (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation).

3.4.2.2 Practice-related Changes

The amplitudes related to rewP (FRN_{diff}) as well as to the FRN (FRN_{peak}) were expected to decrease after five sessions of extensive practice (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation). LFCP-amplitudes were also likely to change but without a directional hypothesis (ibid.). Decreased amplitudes in the last practice session, as compared with the first one, were also predicted for the P300 (ibid.). With respect to frontal theta-band activity, it was anticipated that theta power would likely decrease after five sessions of extensive practice (cf., Margraf et al., 2023, Part II, Chapter III of this dissertation).

3.4.2.3 Short-term Behavioral Adaptations

It was forecasted that larger amplitudes of the FRN (FRN_{peak}) (more negative amplitudes) would likely predict larger short-term behavioral changes (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation). Related to the P300, larger amplitudes (more positive amplitudes) were expected to predict smaller changes of subsequent behavior (ibid.). Larger amplitudes of the LFCP (more positive amplitudes) were likely to predict larger short-term behavioral changes (ibid.). Further, it was expected that the coherence of these components and short-term behavioral changes were likely to change after five sessions of extensive practice, but in an explorative fashion (ibid.). With respect to frontal theta-band activity, it was anticipated that increased theta power was predictive of larger subsequent behavioral changes, especially after negative feedback (cf., Margraf et al., 2023, Part II, Chapter III of this dissertation).

3.4.2.4 Long-term Learning

Long-term learning effects were evaluated as retention performance (accuracy and consistency in the motor task) and with respect to motor automatization (reduction of DTC in the cognitive task). In relation to retention performance, it was expected that larger valence-specific amplitudes of the FRN (FRN_{peak}), the rewP (FRN_{diff}), the P300, and the LFCP were likely to predict better retention performance in the motor task (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation). With respect to motor automatization, it was anticipated that larger amplitudes of the FRN (FRN_{peak}) were likely to induce lower amounts of motor automatization, while larger amplitudes of the rewP (FRN_{diff}) were likely to induce higher amounts of motor automatization (ibid.). In addition, larger amplitudes of the P300 after positive feedback were forecast to be predictive of the degree of motor automatization (ibid.). Regarding the LFCP, it was expected that larger amplitudes are probably predictive of a lower amount of motor automatization (ibid.). Furthermore, lower frontal theta-band activity is anticipated to predict a larger degree of motor automatization, especially in the later practice phase (cf., Margraf et al., 2023, Part II, Chapter III of this dissertation).

3.4.2.5 Correlations of Frontal ERPs and Frontal Theta-band Activity

It was foreseen that frontal theta-band activity would correlate with amplitudes of the FRN ($\mathrm{FRN}_{\mathrm{peak}}$) with respect to both valence categories (positive, negative) (cf., Margraf et al., 2023, Part II, Chapter III of this dissertation). Further, a correlation of LFCP-amplitudes and frontal theta power was expected in an explorative manner (ibid.).

3.5 Summary of Results

The following is a brief summary of the results. A more detailed description and the statistical values can be found in the corresponding references to be found in the cumulus of this dissertation (Part II, Chapters I – III). Moreover, the results will be briefly interpreted and discussed.

3.5.1 Behavioral Results

The participants received positive feedback after approximately 50% of the trials. The manipulation of the bandwidth, therefore, proved to be successful. With respect to the movement time, participants were able to perform the movement sequence below a maximum movement time of 1800 m (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation).

3.5.1.1 Practice-related Results

Concerning the practice phases (Practice 1 – Practice 5), the results revealed that both the absolute[20] and the variable[21] error were significantly lower in Practice 5 as compared with Practice 1. In line with the expectations, participants improved their performance in the motor task over the practice course from early to late sessions. The performance became more

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[20] The absolute error served as measurement of accuracy and was calculated based on the differences between the actual and the target value of each movement reversal of one trial in angular degrees. The mean of the calculated differences of the three movement reversals was used as the absolute error of that trial (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation).

[21] The variable error served as a measurement of consistency and was calculated based on the standard deviations for each of the three movement reversals (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation).

accurate (reduction of the absolute error) and more consistent (reduction of the variable error). As a result of higher accuracy and higher consistency, the performance adaptive bandwidth for positive feedback became smaller. At this point, it should be noted that a smaller bandwidth may have made it more difficult to identify the reversal with the largest deviation. As mentioned in Chapter 3.3, the feedback was given only for the reversal with the largest deviation, without information which reversal was concerned. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

3.5.1.2 Learning-related Results

Learning was related to the retention performance without subsequent augmented feedback after at least one night of sleep after the last practice session, and was evaluated based on three tests (the pre-acquisition test in Session 1, pre-test in Session 2, retention test in Session 7). With respect to the performance in the criterion motor task, the results revealed that after five sessions of extensive practice, participants were already able to increase in accuracy (absolute error in the motor task) from the pre-acquisition to the pre-test but not from the pre-test to the retention test. Regarding the consistency of movement execution (variable error in the motor task), the results were somewhat different. Participants improved in consistency with the initial acquisition phase (from the pre-acquisition test to the pre-test), as well as with the extensive practice phase (from the pre-test to the retention test). However, these results were in line with those found in earlier studies (e.g., Agethen & Krause, 2016; Krause et al., 2018). Moreover, participants performed better in the single-task condition as compared with the dual-task condition, with relation to both the absolute error and the variable error. Therefore, participants were not able to focus mainly on the motor task when there was an additional cognitive task. But as the DTC in the motor task did not change after five sessions of extensive practice, the automatization analyses can be focused on the secondary task (n-back), which will be discussed in the next section. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022b; Part II, Chapter II of this dissertation).

The amount of motor automatization was measured as the reduction of DTC in an additional cognitive task (n-back). With respect to the n-back task (2-back), participants were able to reduce n-back errors from the pre-acquisition test to the pre-test and from the pre-test to the retention test.[22] They also made more errors in the dual-task condition as compared to the single-task condition. However, the difference between errors with the dual-task and single-task conditions was significantly smaller in the retention-test as compared with the pre-acquisition test and the pre-test. Participants were, therefore, able to reduce DTC in the cognitive secondary task.[23] Retention performance with respect to motor automatization revealed a moderate effect on the reduction of DTC as compared with other studies using the same experimental setting (Agethen & Krause, 2016; Krause et al., 2018). This can be explained by the feedback schedule in the current setting serving negative feedback in 50% of the trials in the practice phase. According to the *EPAC Hypothesis* (Krause et al., 2018), negative feedback causes attentional control for movement correction and, consequently, interferes with processes of motor automatization. The process of motor automatization benefits from the lower frequency of augmented feedback during practice (Agethen & Krause, 2016) and a reduction of negative feedback in favor of positive feedback (Krause et al., 2018). Although the feedback schedule in the current setting was suboptimal for motor automatization, it was necessary to be able to evaluate the valence-effects of the ERPs, which are sensitive to expectancy, based on different frequencies (Krigolson, 2018). For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022b; Part II, Chapter II of this dissertation).

3.5.2 Neural Results

3.5.2.1 Valence-dependent Effects

With respect to the ERPs time-locked to feedback onset,[24] there was a negative deflection in the time-window of the FRN (FRN_{peak}) and the rewP (FRN_{diff}) at frontal electrode sites (FCz), a positive deflection in the time-window of the P300 at parietal electrode sites (Pz), and a positive deflection in the time-window of the LFCP at frontal electrode sites (FCz). Regarding the valence-dependency of the ERPs, all expectations could be confirmed. The more

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[22] The mean error per trial was calculated as the mean number of omitted responses to matches and responses to non-matches (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation).

[23] Dual-task costs were calculated as the difference between n-back errors that were made in the single-task and the dual-task conditions (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation).

[24] The ERP components were quantified as the mean amplitude in a time window 20 ms before and after a detected peak in the expected time window for the corresponding component (230-350 ms for the FRN, 250-400 ms for the P300, 450-550 ms for the LFCP) (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation). A more detailed discussion of the most appropriate quantification of the ERPs in the current study can be found in the appendix of this dissertation.

negative amplitudes of the FRN (FRN_{peak}) after negative feedback in the time-window of the rewP (FRN_{diff}) were in line with what was found in other studies (e.g., Joch et al., 2017; Krause et al., 2020). The rewP (FRN_{diff}) was interpreted as a pure valence-effect due to equal frequencies of positive and negative feedback and was assumed to reflect processes of reward-based reinforcement learning. The FRN (FRN_{peak}) was understood as an indicator of a prediction error in reinforcement learning and reflects the disinhibition of the dACC (e.g., Hauser et al., 2014) as a part of the cognitive control network. More negative amplitudes of the FRN(FRN_{peak}) might, therefore, be an indicator of higher attentional processing. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

Regarding the P300, it was assumed that different amplitudes might be an indicator of which information was more suitable for the updating of the representation of the task at hand (context-updating hypothesis, Donchin & Coles, 1988). As the amplitudes of the P300 were more positive after positive feedback in the current study, which was also the case in another study with the same setting (Krause et al., 2020), it was assumed that positive feedback information was more suitable for the updating process. However, the results are contradictory as other studies found more positive amplitudes related to negative feedback (e.g., Pfabigan et al., 2011). Based on this heterogeneous set of results, the type of task and the reliability of the feedback categories might be moderators for the valence-dependency of the P300. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

As expected, the amplitudes of the LFCP were more positive after negative feedback. The LFCP was associated with supervised learning and more complex feedback processing (Cockburn & Holroyd, 2018). It was assumed that processes of supervised learning might be of higher significance with a higher informational level of the feedback, like in the current setting serving information about the direction and magnitude of errors. This is assumed to be indicated by the more positive amplitudes of the LFCP. Studies reporting on the LFCP with respect to feedback processing are rare, so the current results reveal a great need for further replication and investigation of the LFCP-component. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

Frontal theta-band activity has been discussed as a general signal that cognitive control was needed (Cavanagh & Frank, 2014).[25] In the current setting, different results in the valence-dependency between evoked (phase-locked) and induced (non-phase-locked) theta activity were revealed. While the evoked (phase-locked) part of frontal theta-band activity revealed no valence-dependent differences between both feedback conditions, induced (non-phase-locked) frontal theta-band activity showed higher power after negative feedback. It is likely that several processes are reflected in frontal theta-band activity. Evoked frontal theta-band activity seems to be sensitive to information that helps to adjust behavior and, therefore, which primarily processes the quantitative error (that is also contained in the positive feedback display) rather than the qualitative valence of augmented feedback. However, induced frontal theta-band activity seems to respond more to the qualitative feedback information (feedback valence) and reflects the greater need for cognitive control after negative feedback. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2023; Part II, Chapter III of this dissertation).

3.5.2.2 Practice-related Changes

With respect to the practice-related changes of the ERPs, none of the expectations could be confirmed in the current study. It was expected that participants would be able to predict augmented feedback more accurately in the later practice session due to a better evaluation of their own performance. The amplitudes of the FRN (FRN_{peak}), interpreted as an indicator of prediction errors, were consequently expected to decrease with further practice, as has been reported for the cognitive domain (e.g., Bellebaum & Colosio, 2014; Krigolson et al., 2009). This was not the case in the current study. The amplitudes of the FRN (FRN_{peak}) increased after five sessions of extensive practice related to negative feedback, while the amplitudes after positive feedback remained unaltered. As the increase of amplitudes only concerned the negative feedback condition, it is assumed that there was an increase in processes related to prediction errors after negative feedback. This effect might be caused by the performance-adaptive bandwidth in the current study. As the errors became smaller over the course of practice, the bandwidth was smaller in the later practice as compared with the early one (cf. Chapter 3.5.1). Therefore, it was assumed that the smaller errors in the later practice were

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[25] Defined as frequency activity of 4-8 Hz measured at the FCz electrode (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation).

harder to predict than the larger errors in the early practice. There might be other possible explanations but with respect to the current data, the explanation stated above seems to be the most likely one. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

With further practice, it was anticipated that the need for updating the internal representation of the task would be less important. This was assumed to be indicated by decreased P300-amplitudes in the later practice as compared with the earlier practice. While studies in the cognitive domain could confirm this assumption (e.g., Bellebaum & Colosio, 2014), this was not the case regarding the current data, which revealed a valence-independent increase of P300-amplitudes. The updating process does not seem to lose its importance, even after extensive practice. This was explained by the ambiguous and rather difficult feedback information in the current setting. The valence-independent increase of P300-amplitudes might be caused by better capabilities in the interpretation and usability of feedback information to update the internal model. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

With respect to the LFCP, the expectations about practice-related changes after five sessions of extensive practice could also not be supported. No significant changes of LFCP-amplitudes could be observed. It seems that the processing of complex feedback information and mechanisms of supervised learning are of equal importance both in early and late practice phases. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022a; Part II, Chapter I of this dissertation).

Regarding frontal theta-band activity, the evoked (phase-locked) part did not meet the expectations (no practice-related changes), while the induced (non-phase-locked) part decreased after five sessions of extensive practice, as expected. The results related to evoked (phase-locked) frontal theta-band activity were explained by possible difficulties in interpreting the error signal presented in the feedback display. The interpretation of the feedback information did not become easier over the course of practice, indeed, it became more difficult, based on the smaller bandwidth in the later practice as compared with the earlier one. However, in line with several learning theories (e.g., Hikosaka et al., 1999), the induced (non-phase-locked) theta decreased over the course of practice, which was interpreted as a reduced demand for attentional control. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2023; Part II, Chapter III of this dissertation).

3.5.2.3 Short-term Behavioral Adaptations

Augmented feedback is intended to support motor learning. In this context, especially negative feedback aims to inform about possible errors and, as a result, enable a conscious error correction. Therefore, neural correlates of augmented feedback processing are assumed to predict short-term changes of behavior. In the current study, larger amplitudes of the FRN (FRN_{peak}), as an indicator of prediction errors, were predictive of subsequent goal-independent changes (mean reversal change)[26] in the early practice phase. Based on these results, it was assumed that the learning mechanisms of reinforcement learning, reflected in the FRN (FRN_{peak}), may rather follow a trial-and-error strategy. This should be more present in the early practice phase when the internal model of the task was thought to be rather vague (cf. Chapter 2.3). For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022b; Part II, Chapter II of this dissertation).

Surprisingly, larger amplitudes of the P300 were predictive of larger goal-directed changes,[27] independent from the practice phase. This was the case for positive feedback based on the primary quantification of goal-directed changes, and independent of the feedback valence based on the adapted quantification of goal-directed changes. This was only vaguely interpreted. The P300 might be predictive for successful identification of the error to correct it, while the rest of the movement pattern is maintained. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022b; Part II, Chapter II of this dissertation).

However, larger goal-directed changes (change of the maximum error) were also predicted by larger amplitudes of the LFCP in both practice phases based on the primary quantification. This was discussed as a higher significance of quantitative error information for

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[26] The mean reversal change was defined as the change of the movement over all three movement reversals and was calculated as the mean absolute deviation of the concurrent three reversals from the respective goal-values in angular degrees (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation).

[27] Quantified as the change of the maximum error. The primary quantification was based on the change of the maximum error in the next trial measured in angular degrees. The adapted quantification was based on the change of the appropriate reversal with the maximum error in the next trial (cf., Margraf et al., 2022b & 2023; Part II, Chapters II & III of this dissertation).

goal-directed changes based on supervised learning processes leading to attention-dependent error identification and error correction. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022b; Part II, Chapter II of this dissertation). These results should be interpreted with caution based on the suboptimal quantification of the change of the maximum error in the primary analysis (cf., Chapter 3.6.1). Based on the adapted quantification (to be found in the supplements of Margraf et al., 2022b; Part II, Chapter II of this dissertation), the results just missed the level of significance with respect to the predictive value of LFCP-amplitudes for correct changes of the maximum error.

With respect to frontal theta-band activity, the evoked (phase-locked) part revealed no predictive value for subsequent behavioral adaptations, while the induced (non-phase-locked) part was predictive of correct adaptations of the maximum error in the next trial. Induced (non-phase-locked) frontal theta-band activity was, therefore, not only interpreted as a signal that cognitive control is needed, but also as an indicator of how well this was implemented. As the predictive value of induced (non-phase-locked) theta-band activity was independent of the valence category in the earlier practice, while it was limited to negative feedback in the later practice, there seems to be a shift in the information that were processed to correct the error. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2023; Part II, Chapter III of this dissertation).

3.5.2.4 Long-term Learning

It was expected that the neural correlates of valence-dependent processing of augmented feedback would be predictive of long-term learning effects (retention performance; automatization). But none of the ERPs (FRN [FRN_{peak}], rewP [FRN_{diff}], P300, LFCP) could predict better retention performance related to better accuracy (absolute error) and consistency (variable error) in the retention test as compared to the pre-test. Further, except for the LFCP, none of the ERP components (FRN [FRN_{peak}], rewP [FRN_{diff}], P300) were predictive of the degree of motor automatization measured as the reduction of DTC from the pre-test to the retention test. Surprisingly, a larger amount of automatization could be predicted solely based on larger LFCP-amplitudes after positive feedback in the first practice session. Additional correlation analyses revealed that the predictive value of LFCP-amplitudes in the early practice was independent of valence. The processing of error information early in practice, accordingly, seems to be an advantage for motor automatization. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2022b; Part II, Chapter II of this dissertation, and the respective supplements).

With respect to frontal theta-band activity, neither could the expectations about the predictive value of the degree of motor automatization be confirmed, either regarding evoked (phase-locked) theta power or induced (non-phase-locked) theta power. Enhanced frontal theta power might only indicate that cognitive control is needed but did not predict the amount of attentional processing. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2023; Part II, Chapter III of this dissertation).

3.5.2.5 Correlations of Frontal ERPs and Frontal Theta-band Activity

It was assumed that the evoked (phase-locked) part of frontal theta-band activity was the spectral reflection of the ERP (Cohen, 2014). Therefore, analysis was conducted to see whether frontal theta-band activity was correlated with one of the frontal ERPs (FRN [FRN_{peak}], LFCP) in the current setting. The results revealed that frontal theta-band activity is not associated with the FRN (FRN_{peak}), both with respect to the evoked (phase-locked) part and with respect to the induced (non-phase-locked) part. However, there was a positive correlation of the LFCP and evoked (phase-locked) frontal theta power in the last practice session. Further, induced (non-phase-locked) frontal theta power was also associated with LFPC-amplitudes in the first practice session, independent of feedback valence. With respect to the last practice session, there was only a positive correlation of induced (non-phase-locked) frontal theta power and LFCP-amplitudes related to negative feedback. In contrast to what has been assumed elsewhere (e.g., Cavanagh et al., 2010), in the current study, frontal theta-band activity seems to be more associated with supervised learning than with reinforcement learning. Moreover, the results suggest that evoked (phase-locked) frontal theta-band activity might not just be the representation of an ERP in the frequency-domain but a reflection of an independent process. For more information about the statistical values, and a more detailed discussion, refer to the cumulus (Margraf et al., 2023; Part II, Chapter III of this dissertation).

3.6 General Discussion

The current study provided further insights into the neural processing of valence-dependent augmented feedback during the learning and extensive practice of a novel motor task. Considering the current results as a whole, a very complex pattern of involved neural mechanisms underlying valence-dependent feedback-based motor learning emerges. To begin with, it was assumed that the processing of reward/feedback from the cognitive domain is reflected by distinct successive processes close in time, which are reflected by different ERPs (Glazer et al., 2018). Glazer and colleagues (2018) address three ERPs in this context: the FRN (or rewP) reflecting a first reaction to the feedback, the P300 reflecting a subsequent update of working memory, and a late positive potential reflecting an extended processing of the information provided by the feedback. Based on the results of the current study, the assumption of three main steps of reward/feedback processing also seem to account for the processing of augmented feedback in the motor domain, although there are some differences to address. While a late positive potential in the cognitive domain is more observed at centro-parietal sites (Glazer et al., 2018), with LFCP in the motor domain, a frontal component was observed (e.g., Krause et al., 2020; Margraf et al., 2022a; Part II, Chapter I of this dissertation).

However, in the current study, three successive ERPs of augmented feedback processing could be identified, which are associated with distinct cognitive processes: the FRN discussed as an indicator of prediction errors in reinforcement learning (e.g., Glimcher, 2011), the P300 associated with a working memory update (Donchin & Coles, 1988), and the LFCP associated with more complex feedback processing in supervised learning (Cockburn & Holroyd, 2018). Although all ERPs match the expectations with respect to their valence-dependency (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation), it should be noted, that the FRN as a first reaction to the augmented feedback indicated difficulties in clearly separating the valence categories – at least in the early practice, while the P300 and the LFCP revealed clear valence-dependent responses in early and late practice sessions. The first step of augmented feedback processing would be an evaluation of performance based on the valence of the augmented feedback in comparison with own outcome expectations. However, ambiguous feedback information (quantitative error information in combination with qualitative valence categories) early in practice seem to complicate an initial evaluation of the performance, reflected by the FRN (or/and rewP). What follows is a subsequent working memory update, by categorizing the feedback information to integrate the new information into the existing representation, reflected by clear valence-dependent amplitudes of the P300. Finally, the information provided by the augmented feedback is processed in more depth, reflected by the LFCP.

It can be noted that the current results with respect to the valence-dependency of the ERPs are in line with expectations and could replicate the results of a previous study (Krause et al., 2020) using the same experimental setting, but limited to just one rather than five practice sessions. However, it should be considered that the characteristic of the FRN in the current study, as well as in the study of Krause and colleagues (2020), was rather small compared to other studies (e.g., Pfabigan et al., 2014). The negative deflection was also evident with respect to positive feedback. A possible explanation might be the feedback design with the transparent bandwidth overlaying the blue error bar (cf., Margraf et al., 2022a, Part II, Chapter I of this dissertation). It can be assumed that in addition to the binary valence category, the quantitative error information was also processed. This deduction demands further investigation. However, except for the rather small valence effect with respect to the FRN, the current ERP results (FRN, P300, LFCP) are consistent with what is known from other studies (for reviews, see Glazer et al., 2018; San Martin, 2012).

Apart from the ERPs, in the current study, a frontal located response in the theta frequency range (4-8 Hz) could also be revealed that was most prominent at the midline (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). This observation may help to disentangle the rather small valence effect with respect to the FRN as a response to ambiguous feedback information. In relation to frontal theta-band activity, there were dissociative results with respect to evoked (phase-locked) and induced (non-phase-locked) frontal theta-band activity (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). While the induced (non-phase-locked) part of the theta-band response revealed a significant difference regarding the valence categories, the evoked (phase-locked) part did not. These results could indicate two processes, one for the qualitative feedback information and one for the quantitative information. This was not expected, based on previous studies, and requires further investigation.

In line with the *EPAC Hypothesis* (Krause et al., 2018), augmented feedback providing quantitative error information provoked activity across frontal neural components associated with higher attention-related activity (frontal theta-band activity, FRN, LFCP). There are different cognitive learning mechanisms (e.g., reinforcement learning, supervised learning) with respect to motor skill learning (Caligiore et al., 2019). The different learning mechanisms are thought to have specific neural correlates in the human EEG (e.g., FRN, LFCP), which in turn are used to study these processes with respect to the processing of augmented feedback and motor learning. While the FRN is correlated more with reinforcement learning (for a review, see Glazer et al., 2018), the LFCP is discussed more with respect to supervised learning (e.g., Cockburn & Holroyd, 2018). Frontal theta-band activity is thought to be a general signal that attentional control is needed to adapt behavior (e.g., Cavanagh & Frank, 2014). Based on the current results, frontal theta-band activity could not be related to the FRN – as it has been the case in other studies (e.g., Hajihosseini & Holroyd, 2013, Williams et al., 2021) – but to the LFCP. Inconsistencies might be explained by differences in feedback characteristics (i.e., quantitative vs. qualitative feedback information). According to the *Super Learning Hypothesis* (Caligiore et al., 2019), the cognitive mechanisms underlying learning do not work independently but somehow interact with each other. Instead of assigning frontal theta-band activity to one or the other mechanisms (reinforcement learning or supervised learning), it is thought that frontal theta-band activity rather plays a moderating role, one which prioritizes one mechanism over the others. Which mechanism is more supportive for learning might be moderated by different external circumstances, like the feedback design (e.g., qualitative vs. quantitative feedback). In the current setting, the error information (direction and magnitude of the deviation from the goal-value) in the feedback display seems to outweigh the qualitative outcome information (positive or negative). The ambiguity in the current feedback design is assumed to be another moderating factor as the feedback contains no information regarding which of the three reversals it was assigned to. These aspects might induce a higher dominance for the supervised learning mechanism and, therefore, consequently, in the current study, may relate frontal theta-band activity to the LFCP rather than to the FRN.

In conclusion, the current results support the assumption that different neural learning mechanisms do not work independently of each other but are active simultaneously and in interaction with each other (Caligiore et al., 2019). Based on these results, frontal theta-band activity might, thus, be seen as a link between the different learning mechanisms. Based on external circumstances (like augmented feedback information), frontal theta-band activity is likely to indicate which learning strategy is the dominant one (cf., Margraf et al., 2023; Part II Chapter III of this dissertation).

Several stage models of motor learning (e.g., Chein & Schneider, 2012; Hikosaka et al., 1999) propose a decrease of attention-related processing over the course of practice sessions, from early to late practice phases. As a consequence, it is to be expected that activity of frontal neural correlates is associated with higher attention-related processing (frontal theta-band activity, FRN, LFCP) and is likely to decrease when attention-independent representations are established. In the current study, only the induced (non-phase-locked) part of frontal theta-band activity decreased after five sessions of extensive practice, while evoked (phase-locked) frontal theta-band activity and LFCP-amplitudes remained unaltered, and the amplitudes of the FRN even increased (cf., Margraf et al., 2022a & 2023; Part II, Chapters I & III of this dissertation). Thus, the current results regarding practice-related changes after five sessions of extensive practice largely did not meet the expectations. The results reveal a complex development of valence-dependent processing of augmented feedback, which might indicate the involvement of several processes (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). Since comparable studies are lacking, especially in the motor domain, further research is needed (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation). However, these results support the idea of separate, but overlapping processes in frontal feedback processing (e.g., Peterburs et al., 2016), but why all frontal correlates associated with frontal attention-dependent processing do not decrease with an increased amount of automatic control remains to be solved (Margraf et al., 2022b; Part II, Chapter II of this dissertation).

In addition to valence-specific feedback processing and practice-induced changes in neural feedback processing, the current study examined the predictive value of the neural components (frontal theta-band activity, FRN, P300, LFCP) for short-term behavioral adaptations (Margraf et al., 2022b & 2023, Part II, Chapters II & III of this dissertation). The results display complex relationships of processes linked with different learning mechanisms (reinforcement learning, supervised learning) and different moderators (e.g., feedback valence, feedback design). The predictive value of the FRN was limited to the early practice phase and was only related to goal-independent adaptations (Margraf et al., 2022b; Part II, Chapter II of this dissertation). Reinforcement learning processes, therefore, seem to contribute to behavioral adaptations only when the internal model is rather vague, as is likely to be the case in earlier phases of motor learning (cf., Chapter 2.3). Further, it seems that the predictive value of the LFCP is related to goal-directed changes and error-correction, both in the early and in the late practice phase (Margraf et al., 2022b; Part II, Chapter II of this dissertation). In the current study, where quantitative error information was provided with the augmented feedback display, supervised learning processes reflected by the LFCP seem to be of higher significance. In this context, induced (non-phase-locked) frontal theta-band activity seems to be an indicator of how well attentional resources could be implemented for error correction (Margraf et al., 2023; Part II, Chapter III of this dissertation). However, the results with respect to the P300 were somewhat surprising. Larger amplitudes of the P300 forecasted larger goal-directed changes but only with respect to positive feedback (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation). Moreover, larger amplitudes of the P300 preceded incorrect changes of the maximum error (cf., supplements of Margraf et al., 2022b, Part II, Chapter II of this dissertation). The role of the P300 and the update of working memory with respect to behavioral adaptations is not yet clear and demand further investigations.

At this point, the question arises, what are the consequences for long-term learning with respect to retention performance and automatization? As stated above, frontal neural correlates are associated with specific learning mechanisms. While the FRN is related to reinforcement learning (Glimcher, 2011), the LFCP has been discussed with respect to supervised learning (Cockburn & Holroyd, 2018) (cf., Margraf et al., 2022a, Part II, Chapter I of this dissertation). Previous research has suggested that learning based on reinforcement is an advantage in early learning phases (Colino et al., 2020), when a representation of the task is not yet established, and complex feedback information might overwhelm the novice learner. Reinforcement learning should be rather apparent through a trial-and-error strategy in short-term behavioral adaptations. The current study distinguished between goal-independent changes, which relate to the overall change of the movement pattern, and goal-directed changes, which relate to the adjustment of the maximum error (cf., Margraf et al., 2022b, Part II, Chapter II of this dissertation). Related to the early practice phase in the current study, the FRN was predictive of larger goal-independent changes, while there are indications that the LFCP was more predictive of goal-directed changes (ibid.). Participants still seemed to use a trial-and-error strategy, as would be expected in the Formation Stage (Chein & Schneider, 2012). At the same time, however, they already seemed to be able to assign the error information and tried to adjust their movement accordingly, as would be expected in the stage of *controlled execution* (Chein & Schneider, 2012, cf., Chapter 2.3). The findings suggest a transition between the stage of *formation* and the stage of *controlled execution*. This would also be in line with the assumption that supervised learning (associated with the LFCP) supports reinforcement learning (associated with the FRN) during the acquisition of a motor sequence (Caligiore et al., 2019). In the last practice session of the current study, no predictive value of the FRN could be revealed, while there are indications that the predictive value of the LFCP was independent of the practice phase. Processes of supervised learning, indicated by the LFCP, seem to be dominant.

How do these relationships affect long-term learning measured as retention performance and motor automatization? As already mentioned above, the *Super Learning Theory* (Caligiore et al., 2019) proposed that the different neural learning mechanisms (unsupervised learning, supervised learning, reinforcement learning) do not work independently of each other but are simultaneously active. It seems, however, that not all contribute equally to the learning success with respect to retention performance and automatization. In the current research, none of the neural correlates (FRN, P300, LFCP) could predict performance with respect to accuracy and consistency in the retention test with at least one night of sleep after the last practice session (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation). However, it should be noted that participants improved in accuracy over five sessions of extensive practice with subsequent augmented feedback (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation), but this improvement did not affect the test performance in the retention test without subsequent augmented feedback (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation). As postulated by the *Guidance Hypothesis* (Salmoni et al., 1984), high frequent error feedback provokes a dependence on this augmented information and prevents the formation of individual mechanisms for error detection. The current results suggests that the participants relied heavily on augmented quantitative error information to improve their practice performance, and consequently, the performance in the retention test dropped and was comparable to pre-test performance when augmented error information was lacking. The results might be different if the augmented feedback were based on qualitative feedback (positive, negative) without quantitative error information, as it would rather support implicit learning processes (Hinneberg & Hegele, 2022).

However, unlike the retention performance with respect to accuracy and consistency in the retention test, the current results revealed the neural correlates to hold a predictive value with respect to motor automatization measured as the reduction of DTC. A higher degree of motor automaticity could be predicted solely based on LFCP-amplitudes in the early practice phase. The processing of quantitative error information early in practice seems to be beneficial for the reduction of DTC in the retention test (cf., Margraf et al., 2022b; Part II, Chapter II of this dissertation, and the respective supplements).

3.6.1 Limitations of the Current Study

In the following section, some limitations of the current study will be discussed. A first focus should be on the task *per se*, which cannot be generalized for every motor skill. In the current study, participants received no feedback about the overall movement pattern and visual movement control was occluded. Although it was not the goal of the current study to model a real-world task, learning situations with corresponding conditions do exist (e.g., a dancer receiving ambiguous feedback for a sequence of postures). However, it should be considered that there are learning situations as well, in which feedback on the whole outcome of the performance is provided (e.g., a basketball player can see directly if their throw was successful when the ball has hit the basket). In future research, the task conditions should be changed so that the setting would correspond to other learning situations as well (e.g., with visual movement control or by giving feedback related to the movement as a whole). This kind of research may help to gain a deeper understanding of characteristics of neural correlates of augmented feedback processing which are generalizable to several motor learning tasks, and which are specific to specific learning conditions. This point was also discussed by Margraf and colleagues (2023; Part II, Chapter III of this dissertation).

Another aspect concerning the type of task is the high demand for accuracy and consistency. It is to be expected that it is impossible for human beings to consistently hit the reversals at the required angles (70°, 20°, 70°). At a certain performance level, no further improvement might be possible, and a constant margin of error remains (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). Whether this level has already been reached within the five practice sessions in the current experimental design can be examined by an evaluation of the performance across the single practice sessions (from Practice 1 to Practice 5, instead of only Practice 1 and Practice 5). However, in another study using the same experimental setting but with another feedback design (normative feedback), participants were able to reduce the error to a larger extent as compared with the current data (Zobe et al., 2019). The motivation of the participants for further improvements could play a crucial role in determining the extent to which further developments are possible (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). Moreover, the limit to which further improvements are possible might vary from person to person. Some people may be able to improve more and/or more quickly than others. However, this also applies for real-life learning situations.

Next, the feedback design in the current study should be discussed, as this was ambiguous in two aspects. First, there were no clear valence categories in the feedback display (*feedback complexity*; Faßbender et al., 2023), and second, there was no information regarding which of the three reversals it referred to (*assignment ambiguity*, Faßbender et al., 2023). Related to the first aspect, caused by the transparency of the bandwidth, quantitative error information was also transported with the positive feedback display. This may have resulted in it being more difficult for participants to form clear valence categories (*feedback precision ambiguity*; Faßbender et al., 2023). It could also be the case that some participants ignored the error information served by the positive feedback display, while others did not. This may have had an impact on the neural feedback processing. In the current study, it has been argued that the FRN was sensitive to this manipulation, resulting in relatively small valence effects, especially in the early practice as compared with other studies (e.g., Pfabigan et al., 2014; cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation). Further, the negative deflection was also evident after positive feedback (cf., Margraf et al., 2022a; Part II, Chapter I of this dissertation). Whether the results of the FRN can really be attributed to the feedback design should be examined by a follow-up study with clear valence categories.

Related to the second aspect, the augmented feedback was referred to the reversal with the largest deviation from the goal value, without stating to which of the three reversals the feedback belonged. Therefore, the participants could only guess which reversal should be corrected (*response complexity*; Faßbender et al., 2023), but there was no subsequent confirmation if the correct reversal were identified (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). This uncertainty might also have had an influence on the neural processing of augmented feedback. However, it should be noted that in nearly 70% of all cases, participants were able to correctly adjust the largest error (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation, and the respective supplements).

Another aspect to explore concerns the quantification of the goal-directed behavioral change. As discussed in the supplements of Margraf and colleagues (2022b; Part II, Chapter II of this dissertation), the primary quantification of the goal-directed behavioral change (maxAE change) was not suitable to estimate goal-directed changes. To deal with this issue, the quantification was adjusted by no longer distinguishing between large and small changes based on the individual median, but rather between correct und incorrect adjustments of the largest error in the next trial (cf., Margraf et al., 2023; Part II, Chapter III of this dissertation). However, this adjustment unfortunately leads to unequal amounts of trials in the respective conditions. There was a mean of 69.30% correct trials in each valence category and per practice session. With respect to the ERPs that are sensitive to expectancy (e.g., FRN, P300), this should not be problematic as the distribution was applied retrospectively and not during the recording. However, this unequal distribution could probably be problematic in terms of the statistical evaluation. For future evaluations, the quantification of the goal-directed change should be thoroughly reconsidered to find a more appropriate solution. With respect to the current study the results should therefore be interpreted with caution and replications of the results are highly recommended.

3.6.2 Conclusions and Future Directions

The current dissertation project is, as far as known, the first to investigate the neural correlates (FRN, P300, LFCP, frontal theta-band activity) during the extensive practice and learning of a novel motor task. As in the cognitive domain (Glazer et al., 2018), three successive ERPs of augmented feedback processing could be identified (FRN, P300, LFCP), which are associated with distinct cognitive processes (reinforcement learning [Glimcher, 2011], working memory update [Donchin & Coles, 1988], supervised learning [Cockburn & Holroyd, 2018]). Further, frontal theta-band activity, interpreted as a signal that cognitive control is needed (Cavanagh & Frank, 2014), was captured. While the valence-dependency of the distinct components widely matched the expectations, there were surprising results with respect to practice-induced changes, and further with respect to short-term behavioral adaptations and long-term learning effects. However, although many questions remain unanswered, the study provided many aspects which will assist follow-up research, to achieve a better understanding of the neural mechanisms underlying valence-dependent feedback processing in motor practice.

It is argued that the processing of any kind of error information early in practice is advantageous for the reduction of DTC, as it might support a quick development of a stable representation of the movement (cf. Margraf et al., 2022b; Part II, Chapter II). This implies that those persons, who were able to establish a stable representation early in practice, may also be able to reduce attention-dependent processing earlier during the practice phase, as compared with people, who only built up a stable task representation later on. However, there is evidence that there are individual differences in the reduction of DTC (e.g., Ruthruff et al., 2006). A possible explanation may be found in genetic variations in the dopaminergic metabolism. In this context, the catechol-O-methyltransferase (COMT) is responsible for the degradation of dopamine in the PFC (e.g., Chen et al., 2004). Thereby, the COMT Val158Met polymorphism influences how fast dopamine is metabolized, that is, how long dopamine is available in the PFC (Chen et al., 2004; Nogueira et al., 2019). The Met allele is associated with higher dopamine availability and, therefore, assumed to enable an advantage in tasks that require stability (Nogueira et al., 2019), such as the practice of accuracy and consistency. In a post-hoc analysis, Krause and colleagues (2014) have already found indications that the COMT-genotype was related to the level of dual-task reduction (i.e., automatization) in a group of participants acquired from different studies in the same experimental setting. This could be a promising approach for further research to understand the neural mechanisms underlying valence-dependent feedback processing as completely as possible.

It is assumed that delayed augmented feedback facilitates retention performance as compared to immediate augmented feedback (Swinnen et al., 1990). Based on theoretical considerations, it is proposed that short feedback delays provoke slower processes based on implicit learning, while long feedback delays provoke faster processes based on explicit learning (Hinneberg & Hegele, 2020). In the current setting, feedback was presented after the closure of the time-window for movement execution (Margraf et al., 2022a, Part II, Chapter I of this dissertation). Depending on when participants started the movement after the start signal (color change of the upper bar from red to green in combination with an acoustic tone), the augmented feedback was presented with a delay of between 1000 ms and 2000 ms. An important issue with respect to future research should be to investigate how the manipulation of the feedback delay affects the characteristics of the neural correlates associated with different learning mechanisms.

Finally, it should be noted that from the methodological side, not all neural processes could be captured by ERP-analysis. To analyze EEG data carefully, an analysis of the ERPs as well as a time-frequency analysis is recommended. Since there are many differences and aspects to consider, especially due to the analysis of time-frequencies, uniform standards are urgently needed to make results comparable.

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PART II – CUMULUS

Chapter I

Valence-dependent neural correlates of augmented feedback processing in extensive motor sequence learning – Part I: Practice-related changes of feedback processing

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Abstract

Several event-related potentials (ERPs) are associated with the processing of valence-dependent augmented feedback during the practice of motor tasks. In this study, 38 students learned a sequential arm-movement-task with 192 trials in each of five practice sessions (960 practice trials in total), to examine practice-related changes in neural feedback processing. Electroencephalogram (EEG) was recorded in the first and last practice session. An adaptive bandwidth for movement accuracy led to equal amounts of positive and negative feedback. A frontal located negative deflection in the time window of the feedback-related negativity (FRN) was more negative for negative feedback and might reflect reward prediction errors in reinforcement learning. This negativity increased after extensive practice, which might indicate that smaller errors are harder to identify in the later phase. The late fronto-central positivity (LFCP) was more positive for negative feedback and is assumed to be associated with supervised learning and behavioral adaptations based on feedback with higher complexity. No practice-related changes of the LFCP were observed, which suggests that complex feedback is processed independent from the practice phase. The P300 displayed a more positive activation for positive feedback, which might be interpreted as the higher significance of positive feedback for the updating of internal models in this setting. A valence-independent increase of the P300 amplitude after practice might reflect an improved ability to update the internal representation based on feedback information. These results demonstrate that valence-dependent neural feedback processing changes with extensive practice of a novel motor task. Dissociating changes in latencies of different components support the assumption that they are related to distinct mechanisms of feedback-dependent learning.

Introduction

The practice of a motor task is usually supported by external feedback (e.g., augmented feedback from a coach or therapist), intended to facilitate learning. There are several characteristics of augmented feedback (e.g., feedback timing: Swinnen et al., 1990; feedback frequency: Marschall et al., 2007; feedback valence: Zobe et al., 2019) that can be manipulated and therefore, it is important to consider how these characteristics affect motor practice and learning. The present study focusses on the feedback valence (positive vs. negative), as it is known to have strong effects on motor learning and automatization (Agethen and Krause, 2016; Krause et al., 2018; Wulf et al., 2010; Zobe et al., 2019).

Valence-Dependent Processing of Augmented Feedback in Motor Learning

Motor practice should promote automatization as a specific dimension of learning, as characterized by reduced involvement of attentional control processes (Fitts and Posner, 1967; Hikosaka et al., 1999; Poldrack et al., 2005). During initial learning stages, attentional control processes are highly involved and motor execution is based on abstract effector-independent representations (e.g., representations in a spatial code). With more practice, attentional control is tuned down, while automatic control processes take over and become more and more operative, and motor execution is based on effector-specific representations (e.g., representations in a motor code) (Hikosaka et al., 1999; Rémy et al., 2010). Related to valence-dependent augmented feedback, the error-provoked attentional control hypothesis (EPAC hypothesis), stated by Krause et al. (2018), assumes that negative augmented feedback provokes attentional control processes for movement correction and therefore, hampers motor automatization, especially in the later learning stages (cf. also Agethen and Krause, 2016). Whereas feedback with positive valence seems to promote learning via long-term potentiation of neural activation patterns that led to the positive feedback event (reward-prediction-error-hypothesis of dopamine: Glimcher, 2011; Schultz et al., 1997).

Changes in Neural Substrates and Information Processing During Motor Learning

Changes in information processing during motor learning are accompanied by structural changes in the brain and a shift of involved neural substrates (Doyon et al., 2009; Toni et al., 1998). In the early practice, the dorsal prefrontal cortex (PFC) and the anterior cingulate cortex (ACC), as components of a cognitive control network, are highly activated, as well as rostral-dorsal (associative) areas of the striatum (Chein and Schneider, 2012; Jueptner et al., 1997; Lohse et al., 2014). Over the course of practice, there is a shift in neural activation. So, in the later practice, when the movement sequence becomes more automatic and performance increases, the activation of the PFC and the ACC is diminished, while there is more activation of the caudal-ventral (sensorimotor) areas of the striatum (Grafton et al., 1995; Jueptner et al., 1997). These substrates are also involved in the processing of feedback information (Glimcher, 2011; Holroyd and Coles, 2002) and changes in active neural substrates might therefore reflect motor-learning-related alterations of augmented feedback processing.

When examining augmented feedback in the learning context, qualitative (e.g., binary feedback as “hit” vs. “miss”) and/or quantitative (e.g., complex feedback about the magnitude and the direction of the error) feedback information needs to be considered. It is not yet clear which feedback information is more supportive, in general terms and with respect to a specific learning phase, or even with respect to a particular task. These informational components of feedback can be associated with different learning mechanisms (i.e., reinforcement learning [Glimcher, 2011] and supervised learning [Cockburn and Holroyd, 2018]). For a better understanding, the principle of reinforcement learning is explained in more detail: Future prediction is a key aspect of behavioral control and in motor learning. One usually behaves in a way to get reward and to avoid punishment (or to get positive feedback and to avoid negative feedback). This interaction of prediction and outcome is described in the reward-prediction-error hypothesis (Glimcher, 2011; Schultz et al., 1997). It is postulated that, if an action leads to an outcome that is perceived to be better than expected (i.e., positive reward prediction error), then dopaminergic midbrain neurons increase their firing frequency above the basal rate. The increased dopamine level is an important signal for long-term potentiation and learning. Otherwise, if an action leads to an outcome that is worse than expected (i.e., negative reward prediction error), the dopaminergic firing rate drops below the basal rate and causes a disinhibition of the dorsal ACC (as part of the cognitive control network for behavioural adaptation). These striatal-cortical neural mechanisms are the basis of reinforcement learning (Glimcher, 2011; Holroyd and Coles, 2002). In supervised learning, a desired output pattern (e.g., an action plan) is compared to the current output pattern (Caligiore et al., 2019). Based on the discrepancy between the desired and the current output, learning is induced via cerebellar-cortical networks (Caligiore et al., 2019). Hence, reinforcement learning can be described as learning to predict rewards, whereas supervised learning can be described as learning based on the minimization of errors.

Reinforcement learning (Sutton and Barto, 1998) can be assumed to be guided by qualitative feedback information and has been shown to promote the acquisition of a simple reaching task, when compared to quantitative feedback, which is assumed to promote supervised learning (Colino et al., 2020). In contrast, qualitative (i.e., binary) feedback on success was rather shown as a benefit in stabilizing motor adaptation (after initial practice), when compared to feedback containing error information (Shmuelof et al., 2017). As Colino et al. (2020) themselves give different alternative explanations for the qualitative feedback advantage in their experimental setting, it is doubtful that reinforcement learning in general is of higher importance in the early learning stages. This might be especially the case for less complex motor tasks, whereas more complex tasks might demand for more complex declarative processes (e.g., supervised learning). Supervised learning based on quantitative feedback might induce the acquisition of an underlying task structure more effectively, which itself produces costs in the early stages of learning (Collins, 2017), and in turn, can explain performance disadvantages of quantitative feedback in learning experiments with a limited amount of practice. Consistent with this perspective, neurophysiological findings document a shift from cerebellar-cortical networks (associated with supervised learning) to striatal-cortical networks (associated with reinforcement learning) (Caligiore et al., 2019).

Event-Related-Potentials (ERPs) as Neural Signatures of Feedback Processing

There are several components of the human event-related potential (ERP) that are associated with the processing of valence-dependent augmented feedback during the practice of several kinds of tasks, and thus, also for motor tasks. In the following section, distinct ERPs and their function with respect to different mechanisms of processing augmented feedback (e.g., reinforcement learning and supervised learning) will be described. If and how these processes might change after extensive practice and improvement of performance is not yet fully understood. In fact, to the best of our knowledge, there are no studies on neural changes in feedback processing after extensive practice in the context of motor learning (i.e., after multiple sessions of practice with consolidation phases).

The Feedback-Related Negativity (FRN)

The feedback-related negativity (FRN) occurs about 250 ms after feedback onset above frontal electrode sites (Krigolson, 2018; Miltner et al., 1997; San Martin, 2012). Its origin is assumed to be the dorsal anterior cingulate cortex (dACC), localized in frontal areas of the brain (Bellebaum and Daum, 2008; Hauser et al., 2014). According to the reinforcement learning theory, the FRN is often discussed as an indicator of a prediction error independent from valence (Alexander and Brown, 2011) and reflects the down-regulation of dopaminergic midbrain neurons, which leads to a disinhibition of the dACC (Glimcher, 2011; Schultz et al., 1997). With regard to the source of the FRN (i.e., dACC), it can be assumed that it is associated to processes that hamper motor automatization after feedback with negative valence, as it might activate frontal areas belonging to the cognitive control network (Agethen and Krause, 2016; Krause et al., 2018; Zobe et al., 2019). Although the FRN might reflect positive as well as negative prediction errors, findings consistently reveal more negative activation for negative feedback compared to positive feedback (for a review: Glazer et al., 2018; San Martin, 2012). However, it should be noted, that it is still a matter of debate whether it is really a negativity, or rather a reward positivity (RewP, Hajcak Proudfit, 2015; Krigolson, 2018). There are arguments stating that an N200-like component is a baseline response to feedback and that this basic negativity is attenuated by rewards (for a review: Hajcak Proudfit, 2015).

In this regard, some authors differentiate two subcomponents of the FRN (e.g., Höltje and Mecklinger, 2020; Peterburs et al., 2016). Peterburs et al. (2016) revealed a dissociation of the peak-to-peak measure from P200 to N200 (FRN_{peak}) and the valence-dependent difference-wave in the FRN interval (FRN_{diff}) in a probabilistic learning paradigm. They found that both variables were differentially affected by feedback timing, which led to the assumption that there are two independent but overlapping processes. While the FRN_{peak} might reflect the prediction error, the FRN_{diff} might reflect reward-related processing, which might justify to rather call the FRN_{diff} a reward positivity (RewP). Therefore, in the following, we differentiate between the FRN_{diff} (equals the RewP) as a valence-dependent difference measure, reflecting reward-related processes and the FRN_{peak} as the negativity caused by a feedback-related prediction error.

Following the extensive research in the cognitive domain, research in the motor domain has began to examine the occurrence and functional relevance of the FRN components for feedback processing in motor learning (e.g., discrete arm-movement sequence: Krause et al., 2020; key-press sequence: Loehr et al., 2015; goal-directed throwing: Frömer et al., 2016; Joch et al., 2017 & 2018; Maurer et al., 2019; goal-directed pointing: Colino et al., 2020; Reuter et al., 2018; postural-control task: Torrecillos et al., 2014). Notably, none of these studies integrated more than one session of practice or more than one EEG-recording. Although, some studies integrated a high amount of trials within one single session, there were no phases for sleep-related consolidation (Walker and Stickgold, 2004), which is crucial when learning (defined as relative permanent changes in motor-related memory) is being examined (Schmidt and Lee, 2011). There are two exceptions in terms of scheduling more than one practice session: Maurer et al. (2019) recorded EEG over three sessions, but did not analyze any time-related effects. Joch et al. (2018) analyzed neural data of two consecutive sessions within the same experimental setting, but the two sessions differed in feedback manipulation. It is therefore unknown, how the FRN_{diff} and the FRN_{peak} are altered in motor learning across several practice sessions.

With respect to practice-related changes, in the cognitive domain (e.g., probabilistic learning, decision making, etc.) a decrease of the FRN (which is commonly related to the FRN_{diff} subcomponent) is evident and explained by an increased ability to predict feedback valence (e.g., visual categorization task: Krigolson et al., 2009; for a review see Walsh and Anderson, 2012). Another way of interpretation would be to assume a reduced sensitivity to rewards, if the measured FRN in these studies is dominantly affected by the FRN_{diff} subcomponent. According to this view, the reduction of the FRN_{peak} would reflect an increase in the ability to predict errors. In the motor domain, Joch et al. (2017), as well as Krause et al. (2020), analysed changes, but could not detect a decrease within a single practice session.

Late Fronto-Central Positivity (LFCP)

A component, that is rather rarely reported, is the so-called (late) fronto-central positivity (FCP/ LFCP), occurring above fronto-central electrode sites. Its temporal occurrence seems to vary in dependence of the task. While in the cognitive domain, the component peaks around 400 ms (Arbel et al., 2013; Cockburn and Holroyd, 2018), whereas in the motor domain, the LFCP was observed about 450-550 ms after feedback-onset (Krause et al., 2020). Such temporal inconsistencies might be due to differences in the cognitive load relative to the complexity of feedback processing (Krause et al., 2020).

The LFCP, as reported so far, is sensitive to feedback valence, being more positive after negative feedback, and is assumed to be related to supervised learning processes (e.g., Arbel et al., 2013; Cockburn and Holroyd, 2018; Krause et al., 2020), where cerebellar-cortical networks are involved to process information to integrate the difference between the actual and the desired outcome of behavior (Caligiore et al., 2019).

With regard to practice-related changes, Krause et al. (2020) reported a tendency (p = .061; η^2_p = .15) for a valence-dependent increase within one session of practice, but discussed it as being caused by the underlying increase of the P300. From a theoretical perspective, the LFCP might increase to some point, as the processing of complex (quantitative) feedback develops over the initial phase of practice, and might then decrease again, as supervised learning processes become less important in the later stages of practice, when the difference between the actual and desired outcome becomes smaller. This would be consistent with findings of a shift from cerebellar-cortical networks (associated with supervised learning) to striatal-cortical networks (associated with reinforcement learning) (Caligiore et al., 2019).

P300

The P300 is a positive deflection, peaking about 300 ms up to 600 ms after feedback onset over central-parietal midline electrodes. The P300 is a widely studied component and can be elicited throughout many cognitive tasks (Glazer et al., 2018; San Martin, 2012). The most prominent approach concerning the function of the P300 is the context-updating hypothesis (Donchin and Coles, 1988; Glazer et al., 2018; San Martin, 2012). In accordance with this hypothesis and with respect to motor learning, the component would be an indicator for updating the internal representation of the movement task.

There is evidence that the P300 is valence-dependent, although it is not yet clear under which conditions the amplitude is larger for negative or positive feedback (for a review: San Martin, 2012). With respect to feedback processing in motor learning tasks, there is evidence that the P300 is more positive for positive feedback (Krause et al., 2020). If expectancy (as modulated by frequency) of positive and negative feedback events is equal, valence-effects in the P300 might indicate, which valence category is more important for the described memory-related updating process in the respective setting, which is defined by task as well as feedback characteristics (e.g., informational ambiguity of positive and negative feedback; Krause et al., 2020).

Feedback processing for updating the mental representation may differ in the early practice compared to the later practice. Results in this context are inconsistent. In the cognitive domain, a decrease of the amplitude has been reported (Bellebaum and Colosio, 2014; Bellebaum and Daum, 2008; Luque et al., 2012; Sailer et al., 2010). In the motor domain, Krause et al. (2020) found an increase in the P300 and ascribed this inconsistency with other studies to an increase of the usability of feedback information with a certain degree of ambiguity that is typical for feedback related to complex motor tasks, but not for many cognitive tasks, that have been used comprehensively in ERP-related research on feedback processing. This ambiguity might be explained by the general nature of the tasks. While in the cognitive domain, feedback can be often interpreted unambiguously and therefore can be used directly for the updating of internal models, as the learner is able to report if the subsequent button press was correct, or not, when being engaged in a cognitive task. For motor tasks, this is different, however. They can be characterized by having multiple degrees of freedom with innumerable possible task-solution patterns, which makes it more difficult to relate feedback information to a distinct response. In such a case, the updating of an internal model is hard, due to the limited usability of information. This is especially the case when feedback is also somehow ambiguous. After some experience with the motor task, the interpretation of kinaesthetic information is more reliable, and the feedback can be used to update the internal model more effectively. It can be argued, that this might affect the P300 amplitude as a neural correlate of memory-related updating processes. As the increase of the P300 has been already observed during one session (Krause et al., 2020), the P300 might decrease again as the updating of the internal model might become less important, because the internal model becomes increasingly elaborated by experience.

Aim of the Current Study

The current study aims to replicate the results of Krause et al. (2020), examining changes in valence-dependent neural feedback processing in motor learning with an extended practice phase of five (instead of one) practice sessions. Therefore, participants learned a complex movement sequence with the forearm using a lever device, consisting of elbow-extension-flexion movements with three movement reversals at 70°, 20°, and 70°. EEG was recorded in the first and last practice session, in order to analyse valence-dependent feedback processing and its practice-related change.

Behavior-Related Hypotheses

Concerning the practice sessions, it is predicted that participants improve their performance over the course of practice. Deviations from the defined reversals should be reduced (absolute error: *H.AE.1*) and performance should become more consistent (variable error: *H.VE.1*) in the last compared to the first practice session.

Neural Processing-Related Hypotheses

Based on previous findings (e.g., Sambrook and Goslin, 2015), it is predicted that the FRN_{diff} is evident as a valence-dependent amplitude in the time window of 200-300 ms after feedback onset with more negative amplitudes for negative compared to positive feedback (*H.FRN.1*). Independent of valence, we also hypothesize reduced negativity in the last compared to the first practice session, due to an improved ability to predict one's own movement outcome, which should decrease the FRN_{peak} subcomponent (*H.FRN.2*).

For the LFCP, it is predicted, that the amplitude is valence-dependent, with more positive amplitudes for negative compared to positive feedback (*H.LFCP.1*), similar to what was reported in other studies (e.g., Arbel et al., 2013, Cockburn and Holroyd, 2018; Krause et al., 2020). We further hypothesize practice-related changes of the amplitudes (*H.LFCP.2*), but are not able to state a directional hypothesis of these changes, as we are not able to refer to comparable data sets or relate to a well-founded theory for this comparably "new" ERP-component of feedback processing.

Based on the previous research in the motor domain with the same task (e.g., Krause, et al. 2020), it is predicted that the P300-amplitude is valence-dependent with more positive amplitudes for positive compared to negative feedback (*H.P300.1*). We also hypothesize reduced amplitudes in the last compared to the first practice session, due to a reduced need for updating processes, caused by a better representation of the internal model (*H.P300.2*).

In addition, the latencies of the ERPs were evaluated in an explorative analysis. Therefore, no hypotheses are stated here.

Methods

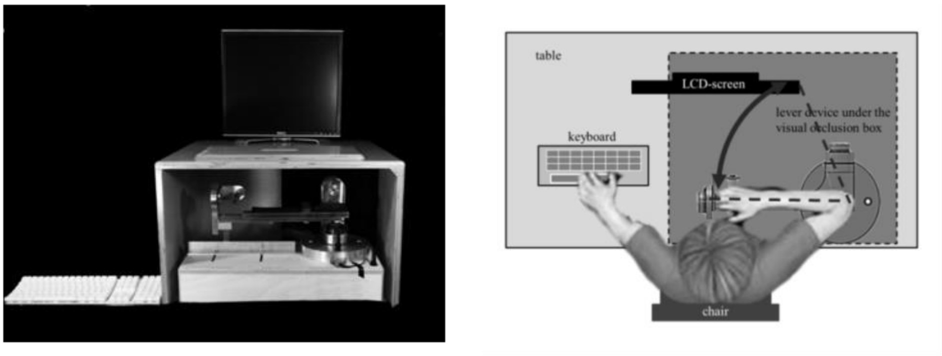
Participants. 43 participants were tested. Five participants were excluded, because of technical problems during EEG recording, too many artifacts in the EEG data, or cancellation of the experiment. The final sample size consisted of 38 undergraduate university students (20 females; mean age = 20.87; age range = 18 – 26 years). Of these participants, 36 were right-handed, as assessed with the German version of the Edinburgh Handedness Inventory (Büsch et al., 2010). Participants were informed about the procedure and gave written consent. All participants had normal or corrected to normal vision and no lesion of the upper limbs. For participation, participants received course credits and they could win up to 25 € for high accuracy. The study was approved by the ethics committee of the German Psychological Society (DGPs).

Apparatus and task. The experimental setup is shown in Figure 1. The movement was performed with an adjustable underarm lever device, which allowed rotational movements in the horizontal plane up to 110 degrees. To measure elbow-joint angles, a linear potentiometer (P6501, Novotech 6500) was attached to the vertical axis of the lever. A power supply unit (Voltkraft PS 1152A) regulated basic voltage at 6V with galvanic separation. An analog-digital converter (Advantech USB 4716; 16 bit, 1000 Hz) transmitted changes in voltage caused by the arm-lever-movements at the potentiometer to a computer. Incoming data was collected by Dasylab 10.0 and converted in angular degrees to measure movement time and movement reversals. Organization of the movement sequences and feedback presentation was realized by a custom-build software (PaDuTas). The visual control of the movements was occluded by a wooden box, which also served as a podium for a monitor (17'', 4:3). A keyboard, placed on the left side of the wooden box, was used as input device for starting the tasks. During the data collection, participants were seated on an adjustable chair.

The criterion task was a right elbow-extension-flexion sequence with three movement reversals at 70°, 20°, and 70°, measured outgoing from a defined position (0°) of the lever device (see Figure 1). The movement sequence was finished by crossing the neutral position (0°) without stopping. The subjects were asked to hit the reversal points as precisely as possible and to keep the movement time (MT) of the 3-movement sequence below 1800 ms.

Figure 1

Apparatus and Experimental Setup



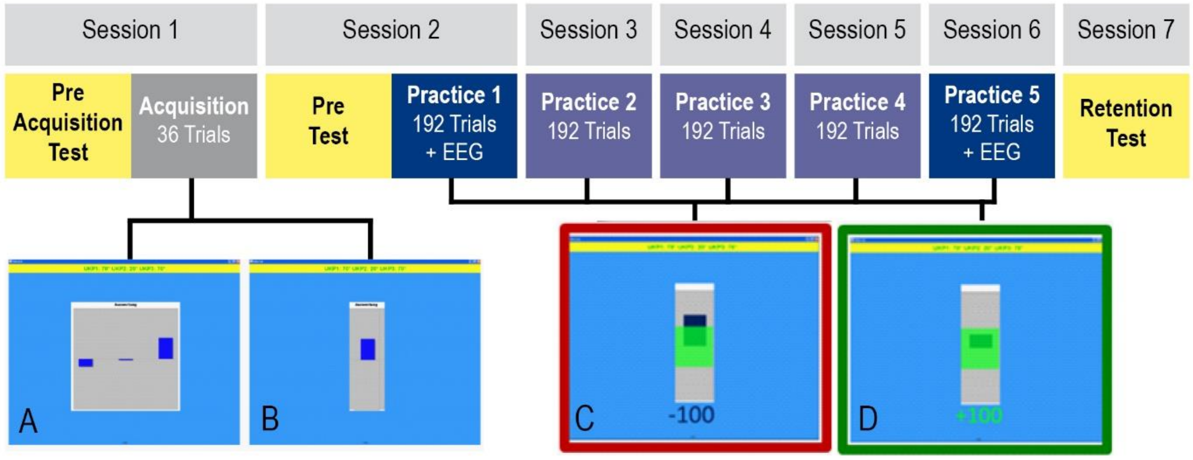
Note: On the left side, the apparatus is shown. The adjustable arm-lever device is placed under a wooden box for visual occlusion, which also serves as a podest for a monitor where instruction slides and feedback presentations are displayed. The keyboard on the left serves as input device for the participant to start the task with the space bar. On the right side, the experimental setup is displayed. The participant is seated in front of the setup with the right arm placed on the lever-device and the left arm placed on the keyboard.

EEG recordings. EEG was recorded with a 16 channel AC/DC amplifier, with active electrodes based on Ag/AgCl sensors (V-amp, Brain Products, Munich, Germany). The scalp electrodes were applied with an electrode cap (actiCAP, Brain Products), according to the 10-20 system. The size of the cap for each participant was chosen depending on his/her head size. Impedances of the electrodes were kept below 20Ω. The active electrodes were placed on F3, FCz, Fz, F4, C3, Cz, C4, P3, Pz, and P4. The ground electrode was set on FPz. Two more electrodes were placed on both mastoids. Online reference was set on FC6. Additional eye electrodes were placed laterally of both eyes, as well as above and below the right eye to measure horizontal and vertical eye movements. EEG data was collected on a separate laptop at a sampling rate of 500 Hz with special software (BrainVision Recorder 2.0, Brain Products, Munich, Germany).

EEG was synchronized to feedback onset. A photodiode (BPW21R, Vishay) attached to a 1.5 cm^2 area in the right lower corner of the feedback screen marked the onset of feedback presentation. The area was shielded with black adhesive tape. Brightness on this screen area changed from dark to light with feedback onset. Data of the photodiode was sampled with the AUX-channel of the amplifier.

Figure 2

Overview of the Experimental Sessions



Note: On the top, the different experimental sessions (1-7) with the respective content are listed. Part I of the study focusses on Session 2 up to Session 6. EEG was recorded in Practice 1 and Practice 5. A: Feedback during the first part of the acquistion (Trials 1 – 12) for each of the three reversals presented as bar graph (with the bar on the left, in the middle, and on the right side representing the feedback for the first, second, and third movement reversal, respectively). The height of the bars corresponds to the magnitude of the error, the direction of the bar (above or below a zero line) shows if the produced angle was too large or too small. B: Feedback during the second part of the acquisition (Trials 13 – 36), showing the same error information as in A, but only for the reversal with the largest deviation; C + D: Feedback presented during the practice phase, the blue bar displays the magnitude and direction of the error for the reversal with the largest deviation, the green transparent bar displays the adaptive bandwidth based on the median of the preceeding block of 12 trials. C displays an example of negative feedback, because the actual performance was outside of the bandwidth, and the participant lost 100 points. D displays an example for positive feedback, because the actual performance was within the bandwidth, and the participant earned 100 points.

Procedures. The study consisted of seven experimental sessions of different lengths, ranging from 30 up to 90 minutes (Figure 2). Participants completed the experiment within 14 days with at least 24 hours between successive sessions. For a better understanding, the following descriptions will focus on the relevant parts of the procedure with respect to the present hypotheses; in detail, acquisition (Session 1) and Practice 1 (Session 2) up to Practice 5 (Session 6). The explanation of the dual-task testing (pre-acquisition test, pre-test, retention) to test the degree of automatization will be explained in detail in the second part of this study (Margraf et al., this issue).

The first session started with the completion of the informed consent form and the pre-experimental questionnaire, including questions about visual acuity, injuries of the upper limbs, and the German version of the Edinburgh Handedness Inventory (Büsch et al., 2010). Further, the head circumference of the participant was measured to choose the size of the EEG-cap. Afterwards, the experimental setup was explained and the seating position was registered, to ensure a replicable position for all sessions. The instruction of the task was done via presentation on the monitor (PowerPoint, Microsoft) and by standardized verbal comments of the experimenter. This way of instruction was maintained for all sessions.

First, the criterion motor task was explained and presented to the participants by an avatar demonstrating the movement five times. After each demonstration, participants were asked to execute the movement themselves. Each trial started with the instruction to bring the arm into the starting position. After 1500 ms a bar at the upper edge of the screen switched from red to green. This marked the start of the interval during which the participants were allowed to execute the motor task (execution interval). After 3000 ms, the bar turned red again, indicating the end of the execution interval. In addition, an acoustic signal marked the change of colors. During the execution interval of 3000 ms, the arm-movement sequence had to be executed within a maximum movement time of 1800 ms (e.g., when movement onset was at 400 ms after the start of the execution interval, movement offset should not be later than 2200 ms after the start of the execution interval). Afterwards, they received feedback about the deviation from the reversals (see Figure 2, A). In cases where the maximum movement time was exceeded, additional information about the movement time was presented in a yellow bar at the upper edge of the screen.

Feedback was given as a bar graph, indicating the direction and magnitude of error for each of the three reversals (the feedback information was altered in the main intervention phase, see Figure 2). The first sessions ended with a first short practice block of 36 trials. From Trials 1-12 of the practice block, participants received feedback about the deviations for each reversal, for the remaining trials (Trials 13-36), they only received feedback for the reversal with the largest deviation, but without information about which reversal it belonged to (see Figure 2, A+B). Feedback was reduced to only one error bar to enable a more unambiguous manipulation of valence with clear binary categories in the main experimental phase. Information on the identity of the reversal was withheld, as some ambiguity in feedback mapping (assignment of feedback to particular movement elements) is characteristic for motor tasks, which is described as the problem of motor redundancy (e.g., Bernstein, 1967; see also Latash, 2012). Infinite combinations of elemental variables (e.g., muscle forces; joint rotations) lead to equifinal movement outcomes. Moreover, we argue that the feedback ambiguity makes the task more challenging over an extensive phase of practice, which is important to keep the participants motivation on a high level.

All further sessions started with six warm-up trials of the motor task, without feedback and without data acquisition. Afterwards, each practice session began with 12 trials without augmented feedback followed by four blocks of 48 trials, each with subsequent feedback presentation following the execution interval. There was a self-determined break after every block. Feedback was presented as a blue bar for the reversal with the highest deviation from the goal value. It changed in size and direction in accordance to the size of the deviation. In addition, the feedback was valued using a goal-adaptive bandwidth based on the median of the preceeding block of 12 trials. The goal bandwidth was displayed as a transparent green bar that overlaid the blue feedback bar (see Figure 2, C+D). Participants were told that the bandwidth corresponded to the performance of a reference group of a peer sample. They earned 100 points, if they performed within the given bandwidth, and lost 100 points, if their performance was outside of this bandwidth. The current score was presented every 24 trials. The choice of feedback based on a bandwidth for accuracy was necessary, because we wanted to obtain a comparable number of positive and negative trials for the statistical evaluation. Also, it seems that bandwidth feedback is more supportive for skill learning than qualitative or quantitative feedback (Agethen and Krause, 2016; Badets and Blandin, 2005). EEG was recorded in Session 2 (Practice 1) and Session 6 (Practice 5).

Data analysis. With respect to evaluate the behavioral data, all trials that contained less or more than three reversals were excluded (0.93 % of the total number of 14.592 trials). Trials in which the movement time of 1800 ms was exceeded, were kept, if they were executed within the execution interval of 3000 ms.

Concerning the practice phase, analysis focused on the first and last practice (Session 2 and Session 6). As a measure for movement accuracy, the absolute error in angular degrees was calculated for each trial. The absolute differences between the actual and the target values were calculated for each movement reversal of the trial. The mean absolute error of the three reversals was used as the absolute error of this trial. The mean absolute error was calculated for 8 blocks of 24 trials in each of the two practices. To analyze movement consistency, the variable error was calculated for each of the three reversals as the standard deviation for the 24 trials of each block. Then, the mean variable error of the reversals was calculated.

Analysis of the neuronal data was done with Brain Vision Analyzer 2.0 (Brain Products, Munich, Germany). Raw EEG data was offline filtered with a 0.3 – 20 Hz zero phase shift Butterworth filter and re-referenced to averaged mastoids. Ocular artifacts were corrected by using the semiautomatic mode of the ocular correction algorithm of the Analyzer based on Independent Component Analysis (ICA). Triggers set by the photodiode were exported and imported again after feedback valence was defined. EEG data was segmented time-locked to feedback onset. Epochs started 800 ms before feedback onset and ended 3000 ms after feedback onset. Epochs were baseline corrected with a time window ranging from -600 ms to 0 ms relative to the feedback trigger. Since feedback was displayed after the execution interval had expired after 3000 ms and participants normally start their movement some hundred milliseconds after the start of the execution interval with a maximum movement time of 1800 ms (e.g., a movement onset after 300 ms with a movement time of 1700 ms would lead to a movement offset 400 ms prior to the baseline interval), movement-related activity or artifacts during the baseline interval should not significantly affect the baseline.

The semiautomatic mode of the artifact rejection algorithm of the Brain Vision Analyzer was used to remove segments containing amplitudes exceeding ±75 µV, as well as segments containing fluctuations of amplitudes exceeding 100 µV from peak to peak. The remaining segments were visually inspected twice by two independent raters. Segments evaluated as containing artifacts by both raters were removed. Only participants with 70% artifact-free segments per condition were included to maintain a comparable high number of trials per participant. Overall, 518 segments of a total number of 14485 were removed. Per condition a mean of 3621 segments were analyzed. The data was averaged in terms of valence (positive & negative feedback) and of time (Practice 1 and Practice 5) for each participant. The grand average for each condition was calculated.

As the FRN is maximal over frontal areas and is typically found at the FCz electrode (Krigolson, 2018), all further analysis concerning this component were done at this electrode. The LFCP was analyzed at the FCz, in order to be comparable to other studies (e.g., Arbel et al., 2017; Krause et al., 2020). Analysis for the P300 was done with the Pz electrode data as, the component is most pronounced over midline parietal sites (e.g., Linden, 2005; Polich and Kok, 1995)

The FRN_{diff} is usually quantified as the difference between negative and positive feedback (Krigolson, 2018; Miltner et al., 1997; San Martin, 2012). Based on our feedback design, we decided that this pre-calculation of a difference would not be appropriate for our data. The presented feedback objectively allows a clear distinction between gains and losses (positive and negative feedback), but caused by the transparency of the overlying bandwidth, negative error information (deviation from the reversal) was also transported with positive feedback to some extend. Moreover, the component that is related to the prediction-error (FRN_{peak}) and its practice-related change is only detectable in the original positive and negative waves. Therefore, we quantified the original waveform, separated for positive and negative feedback. In evaluating the original waveforms, there was no conflict in deciding, whether we are dealing with a negativity or a positivity, which is based on the direction of the subtraction of the two waveforms (Hajcak Proudfit, 2015; Krigolson, 2018).

In a first step, we defined the time windows in which the components of interest should occur. Time windows of 230 – 350 ms for the FRN, 450 – 550 ms for the LFCP, and 250 – 400 ms for the P300 were expected. Then, we run the peak detection algorithm of the analyzer for the chosen electrodes (FCz & Pz) in the mentioned time windows to identify the components for each subject. The peaks were controlled and corrected manually. To attenuate the influence of outliers, the components were quantified as the mean amplitude in a time window 20 ms before and after the detected peaks.

Statistical analysis was done with SPSS (IBM Statistical Package for the Social Science). The alpha level was set to .05 for all analyses. Additionally, partial eta squared was calculated as effect size. All results are given as mean values and standard deviations.

For the behavioral data, two ANOVAs with repeated measures on *practice block* (1-8) and *practice* (Practice 1, Practice 5) were calculated separately for the absolute error and the variable error. For the ERPs, an ANOVA with repeated measure on *practice* (Practice 1, Practice 5) and *feedback valence* (positive, negative) was calculated separately for each ERP (FRN, LFCP, P300) for the amplitudes and the latencies. Follow-up analyses were conducted with paired *t*-tests. One-tailed *t*-tests based on directed hypotheses were labeled t_1.

Results

Behavioral data

Feedback valence. Participants received positive feedback in 51% of the trials in Practice 1 (*M* = 51.18; *SD* = ±4.3; range: 44-61%), as well as in Practice 5 (*M* = 51.33; *SD* = ±2.6; range: 46 – 59%).

Movement time. Participants were able to execute the motor task within the defined time window. The average movement time was similar in Practice 1 (*M* = 1485.09; *SD* = ±237.33) compared to Practice 5 (*M* = 1504.19; *SD* = ±209.66), $t(1,37) = 5.34$; $p = .597$; $d = 0.09$.

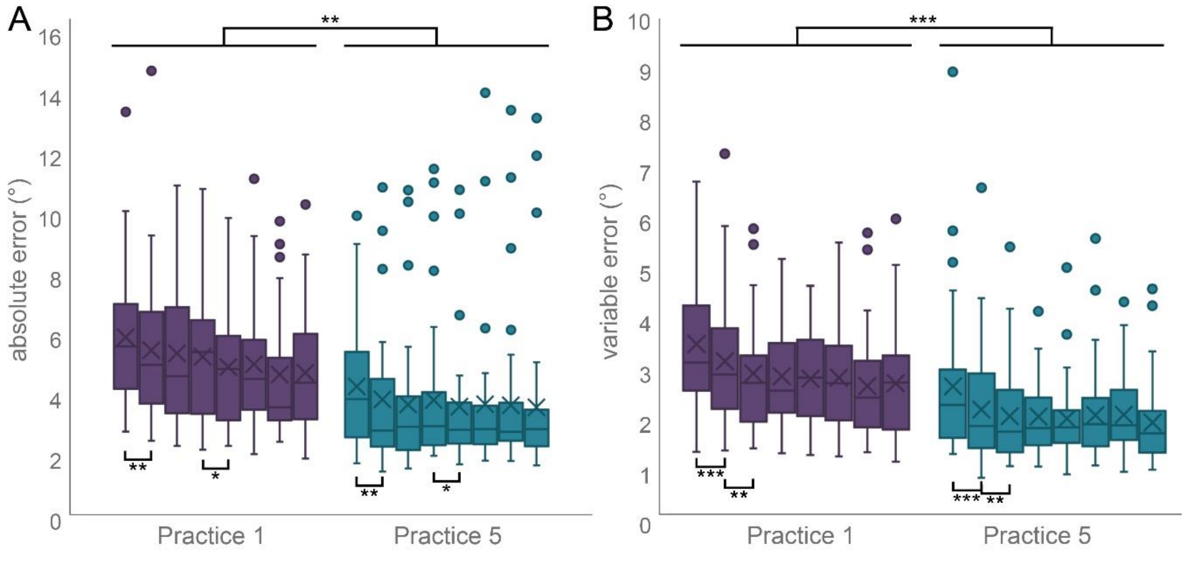
Absolute Error in the Motor Task - Practice. The 2 (*practice*: Practice 1, Practice 5) x 8 (*practice block*: Block 1 to 8) ANOVA for the absolute error showed a main effect for *practice*, $F(2,38) = 10.19$; $p = .003$; $\eta^2_p = .27$. The absolute error was smaller in Practice 5 (*M* = 3.84; *SD* = ±2.24) compared to Practice 1 (*M* = 5.2; *SD* = ±1,64). Furthermore, there was a main effect for *practice block*, $F(2,38) = 5.67$; $p = .002$; $\eta^2_p = .13$. Follow-up analyses for the single comparisons of successive blocks reveal that the absolute error was significantly reduced from Block 1 to Block 2; $t(1,37) = 3.22$; $p = .003$; $d = 0.51$; and from Block 4 to Block 5; $t_1(1,37) = 1.97$; $p = .028$; $d = 0.31$. The hypothesis *H.AE.1* can be supported. The interaction of *practice* x *practice block* was not significant, $F(2,38) = 0.85$; $p = .544$; $\eta^2_p = .02$. The results are displayed in Figure 3 (A).

Variable Error in the Motor Task – Practice. The 2 (*practice*: Practice 1, Practice 5) x 8 (*practice block*: Block 1 to 8) ANOVA for the variable error revealed a main effect for *practice*, $F(2,38) = 18.75$; $p < .001$; $\eta^2_p = .34$. The variable error was smaller in Practice 5 ($M = 2.26$; $SD = \pm0.85$) compared to Practice 1 ($M = 3.04$; $SD = \pm0.85$).

Furthermore, there was a main effect for *practice block*, $F(2,38) = 13.39$; $p < .001$; $\eta^2_p = .27$. Follow-up analyses for the single comparisons of successive blocks reveal that the variable error was significantly reduced from Block 1 to Block 2; $t(1,37) = 4.06$; $p < .001$; $d = 0.67$; and from Block 2 to Block 3; $t(1,37) = 2.75$; $p = .009$; $d = 0.43$. The hypothesis *H.VE.1* can be supported. The interaction of *practice* x *practice block* was not significant, $F(2,38) = 0.51$; $p = .827$; $\eta^2_p = .01$. The results are displayed in Figure 3 (B).

Figure 3

Absolute and Variable Error in the Motor Task

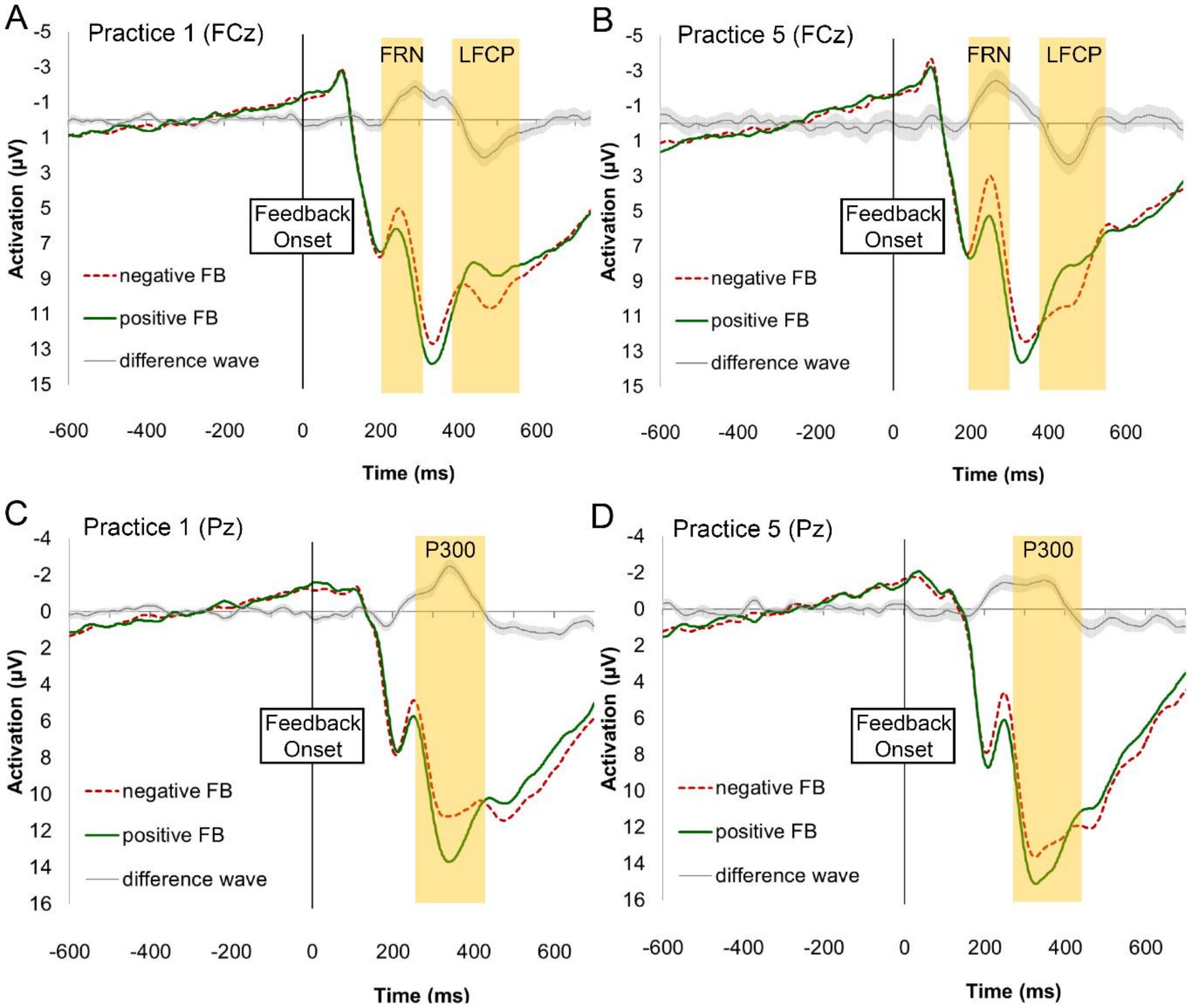


*Note***:** The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box, for **A** the absolute error in angular degrees for Practice 1 and Practice 5, **B** the variable error in angular degrees for Practice 1 and Practice 5. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

Neural Data

Figure 4

ERPs in Practice 1 and 5 at the FCz and the Pz Electrode

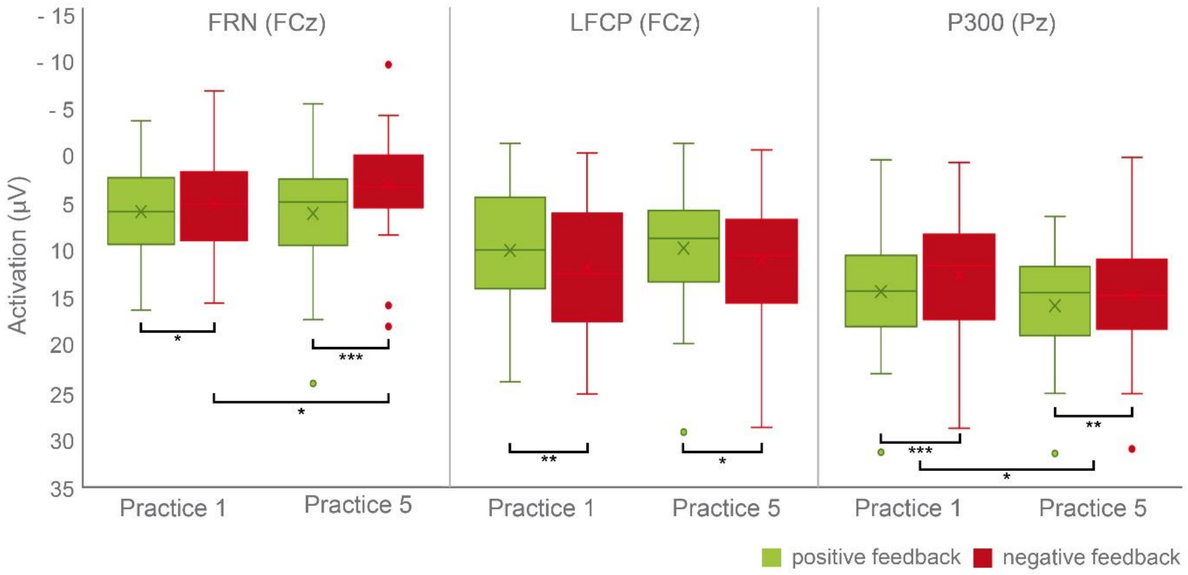


*Note***.** Neural activation in microvolts for positive (green) and negative (red) feedback, time-locked to feedback presentation, for the FCz electrode in Practice 1 (A) and Practice (B), and for the Pz electrode in Practice 1 (C) and Practice 5 (D). Time windows (in milliseconds) of the distinct ERP components (FRN, LFCP, P300) are highlighted. The difference waves were displayed in grey.

FRN (amplitude). The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the frontal negativity in the time window of the FRN at the FCz electrode revealed a main effect for *valence*, $F(1,38) = 30.23$; $p < .001$; $\eta^2_p = .45$ (Figure 4, A and B). The deflection was more negative for negative feedback ($M = 3.88$; $SD = \pm 4.50$) than for positive feedback ($M = 5.86$; $SD = \pm 4.85$). The hypothesis *H.FRN.1* can be supported. Furthermore, the ANOVA revealed an interaction between *practice* and *valence*, $F(1,38) = 10.04$; $p = .003$; $\eta^2_p = .21$. Post-hoc t-tests were computed. The comparison of the differences between negative and positive feedback (which would correspond to the FRN_{diff}) in the respective practice revealed that the difference was larger in Practice 5 (*M* = -3.05; *SD* = ±3.70), than in Practice 1 (*M* = -0.90; *SD* = ±2.20), *t*(1,38) = 3.17; *p* = .003; *d* = 0.51, which would be interpreted as a shift to more negativity. But, if the differences were calculated the other way (positive minus negative feedback, which would correspond to the RewP), there would be a shift into the positive direction. So, to clarify the interaction, post-hoc t-tests, Bonferroni-Holm corrected, for the individual peaks were calculated. This analysis revealed a difference between Practice 1 and Practice 5 with respect to negative feedback, *t*(1,38) = 2.54; *p* = .045; *d* = 0.41, but not for positive feedback, *t*(1,38) = -0.21; *p* = .834; *d* = -0.03, leading to a higher difference in valence-dependent negativity in Practice 5 compared to Practice 1 (Figure 5). This is contrary to the hypothesis *H.FRN.2*. No main effect for *practice* was found, *F*(1,38) = 1.36; *p* = .251; η^2_p = .04.

Figure 5

Activation for Positive and Negative Feedback in Practice 1 to Practice 5



Note: Amplitudes in microvolt for positive (green) and negative (red) feedback for Practice 1 and Practice 5 for the FRN_{peak} (FCz), the LFCP (FCz), and the P300 (Pz). The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

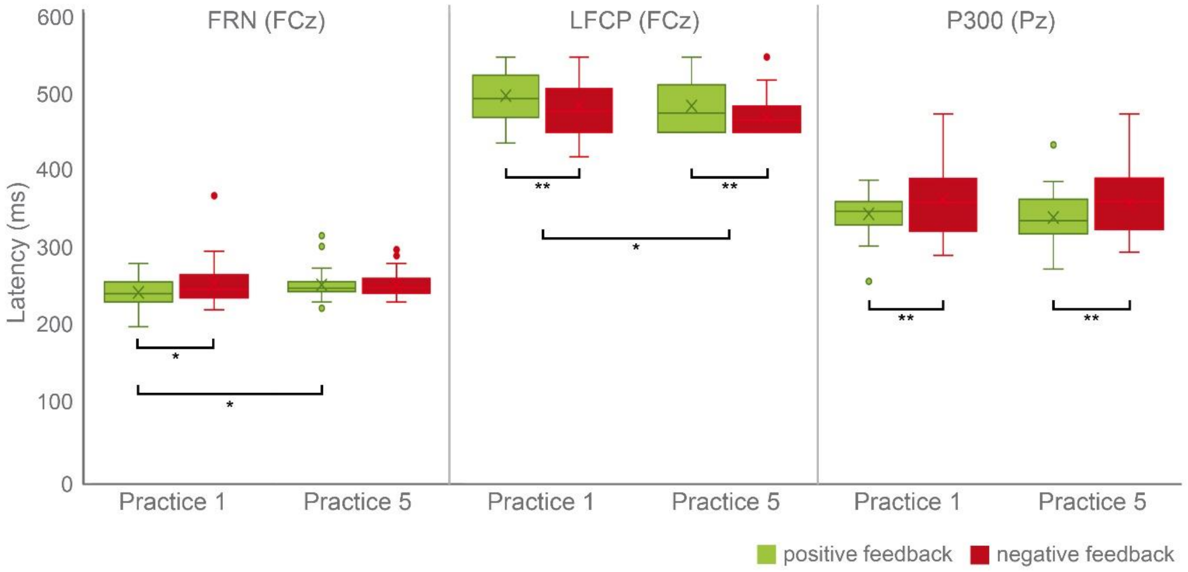
LFCP (amplitude). The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the LFCP measured at the FCz electrode revealed a main effect for *valence*, *F*(1,38) = 17.95; *p* < .001; η^2_p = .31. The deflection was more positive for negative feedback (*M* = 11.19; *SD* = ±5.44) than for positive feedback (*M* = 9.59; *SD* = ±4.66). The hypothesis *H.LFCP.1* can be supported (Figure 4, A and B). No main effect for *practice* was found, *F*(1,38) = 0.20; *p* = .660; η^2_p = .01. The hypothesis *H.LFCP.2* cannot be supported. Moreover, no significant interaction between *practice* and *valence* was found, *F*(1,38) = 0.44; *p* =.512; η^2_p = .01 (Figure 5).

P300 (amplitude). The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the P300 measured at the Pz electrode showed a main effect for *valence*, $F(1,38) = 25.97$; $p < .001$; $\eta^2_p = .41$. The deflection was more positive for positive ($M = 14.88$; $SD = \pm5.17$) than for negative feedback ($M = 13.46$; $SD = \pm5.66$). The hypothesis *H.P300.1* can be supported (Figure 4, C and D). Moreover, there was a main effect for *practice*, $F(1,38) = 6.04$; $p = .019$; $\eta^2_p = .14$ (Figure 5). The P300 was more positive in Practice 5 ($M = 15.04$; $SD = \pm5.67$) compared to Practice 1 ($M = 13.29$; $SD = \pm5.90$). This effect is contrary to the hypothesis *H.P300.2*. No significant interaction between *practice* and *valence* was found, $F(1,38) = 1.07$; $p = .308$; $\eta^2_p = .03$.

FRN (latency). The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the frontal negativity in the time window of the FRN at the FCz electrode revealed a significant interaction between *practice* and *valence*, $F(1,38) = 4.70$; $p = .037$; $\eta^2_p = .11$ (Figure 6). Post-hoc t-tests revealed a significant difference between positive ($M = 242$; $SD = \pm17.59$) and negative feedback ($M = 254$; $SD = \pm26.14$) in Practice 1, $t(1,38) = 2.57$; $p = .014$; $d = 0.42$, but not in Practice 5, $t(1,38) = -0.04$; $p = .969$; $d = 0.06$. Further, a significant difference in the latencies for positive feedback between Practice 1 ($M = 242$; $SD = \pm17.59$) and Practice 5 ($M = 252$; $SD = \pm19.93$) was conducted, $t(1,38) = -2.58$; $p = .014$; $d = 0.48$, this was not the case for negative feedback, $t(1,38) = 0.54$; $p = .595$; $d = 0.09$.

Figure 6

Latencies for Positive and Negative Feedback in Practice 1 to Practice 5



Note: Latencies in milliseconds for positive (green) and negative (red) feedback for Practice 1 and Practice 5 for the FRN$_{peak}$ (FCz), the LFCP (FCz), and the P300 (Pz). The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

LFCP (latency). The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the LFCP at the FCz electrode revealed a main effect for *practice*, $F(1,38) = 6.75$; $p = .013$; $\eta^2_p = .15$, as well as a main effect for *valence*, $F(1,38) = 11.36$; $p = .002$; $\eta^2_p = .24$ (Figure 6). The peak of the LFCP occurred later in Practice 1 ($M = 491$; $SD = \pm 31.63$) compared to Practice 5 ($M = 476$; $SD = \pm 23.49$). Further, the peak after negative feedback was observed earlier ($M = 477$; $SD = \pm 23.45$) compared to positive feedback ($M = 491$; $SD = \pm 27.67$). No other effects were observed.

P300 (latency). The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the P300 at the Pz electrode revealed a main effect for *valence*, $F(1,38) = 10.47$; $p = .003$; $\eta^2_p = .22$ (Figure 6). The peak of the P300 occurred later after negative feedback ($M = 360$; $SD = \pm 37.16$) compared to positive feedback ($M = 342$; $SD = \pm 23.16$). No other effects were observed.

Discussion

Behavioral data

As expected, participants were able to improve their performance over the course of early and late practice. They were able to reduce deviations from the reversals, which indicates that the performance of participants was more accurate at the end of the practice (absolute error: *H.AE.1*). Also, they improved in consistency (variable error: *H.VE.2*). These results are in line with the assumptions on motor skill acquisition (Rémy et al., 2010). As a consequence of higher accuracy, the bandwidth for positive feedback became smaller in the later practice phase, according to the performance adaptive bandwidth value (median of the prior block of 12 practice trials). Furthermore, there was not only an increase in practice performance over the entire intervention (Practice 1 versus Practice 5), but already within one practice session (divided into 8 practice blocks consisting of 24 trials each). In detail, the performance became more accurate after the first practice block within one practice session (Block 1 versus Block 2). Another increase in accuracy was observed after the fourth practice block (Block 4 versus Block 5). With regard to movement consistency, an increase was apparent only in the initial phase of a practice session (Block 1 versus Block 2, Block 2 versus Block 3).

Neural data

FRN

Valence effects. As expected for the ERPs locked to the onset of augmented feedback, more negative amplitudes for negative feedback compared to positive feedback in the FRN time window were observed (*H.FRN.1*), which reflects the existence of a FRN_{diff}. This can be interpreted as a pure valence effect, as the feedback frequencies for the two valence categories were quite similar. This valence-dependent negativity is consistently found in the cognitive domain (e.g., Krigolson, 2018; Miltner et al., 1997; San Martin, 2012), as well as in the motor domain (e.g., Joch et al., 2017; Krause et al., 2020; Van der Helden et al., 2010), and might reflect processes of reinforcement learning as reward-based learning (Glimcher, 2011; Hajcak Proudfit, 2015). The subcomponent $\mathrm{FRN}_{\mathrm{peak}}$ is assumed to reflect the prediction error in reinforcement learning and indicates that the movement outcome was worse than expected after negative feedback or better than expected after positive feedback (Holroyd and Coles, 2002; Schultz et al., 1997). This subcomponent of the FRN reflects the disinhibition of the dACC (Dehaene et al., 1994; Hauser et al., 2014; Miltner et al., 1997), as a part of the cognitive control network (Chein and Schneider, 2012). Therefore, the higher negativity after negative feedback can also be interpreted as being associated with an initial process to induce an increase of attentional processing, in order to reduce the error in future events, which might be more pronounced after negative feedback, a notion, which is in line with the EPAC-Hypothesis (Krause et al., 2018).

At this point, it has to be considered, however, that the characteristic of the ERP in the earlier practice was rather small, compared to other studies using other tasks (e.g., probabilistic gambling task: Pfabigan et al., 2011; time-estimation task: Cockburn and Holroyd, 2018). The negative deflection in the present study was also evident after positive feedback. This was also found in other studies using the same setting (e.g., Krause et al., 2020). The different results might be caused by the feedback design. In the current study, as well as in the study of Krause et al. (2020), complex feedback information was presented (direction and magnitude of the error), and this information was also transported with positive feedback (transparent bandwidth in the visualization of positive feedback), whereas the study of Pfabigan et al. (2011) was based on binary feedback. Cockburn and Holroyd (2018) namely examined different types of feedback (binary, direction, magnitude, full), but only with regard to the presentation of negative feedback. The question if the ambiguity in the present feedback design had caused the small pronounced $\mathrm{FRN}_{\mathrm{peak}}$-characteristic in the present study, could be verified by an additional feedback condition. In the same setting, the $\mathrm{FRN}_{\mathrm{peak}}$ should be more pronounced, if the bandwidth was opaque and so corresponds to a binary feedback condition.

Practice-related changes. The amplitudes in the time window of the $\mathrm{FRN}_{\mathrm{peak}}$ were predicted to decrease over the course of practice. We expected that participants increase their ability to evaluate one's own performance to predict augmented feedback more accurately. Therefore, the $\mathrm{FRN}_{\mathrm{peak}}$, being an indicator of a prediction error, should have been decreased (*H.FRN.2*), as it has been found in other experiments (e.g., object naming: Bellebaum and Colosio, 2014; visual categorization task: Krigolson et al., 2009; probabilistic learning: Luque et al., 2012; decision making sequence learning: Sailer et al., 2010; for a review see Walsh and Anderson, 2012). This was not the case in the current experiment. Other studies also failed to find a practice-related decrease of the FRN in motor learning (Joch et al., 2017), but only for a one-session experiment. Contrary to our assumption, the negative deflection after negative feedback even increased after extensive practice in the present study. As the activation after negative feedback in the FRN time window becomes more negative after extensive practice, while the activation of positive feedback remains unaltered, we interpret this as an increased $\mathrm{FRN}_{\mathrm{peak}}$ after negative feedback. We assume that this effect might reflect an increase in processes related to prediction errors after negative feedback. Altered reward-based processing would have been reflected in a change of the activation after positive feedback in the FRN time window, which is not apparent here.

It is doubtful that an increase of the $\mathrm{FRN}_{\mathrm{peak}}$ to the fifth session of practice indicates any decrease in error detection capability. Instead, we assume that the performance-adaptive bandwidth for positive feedback might have caused this effect. On average, the errors that provoke negative feedback in the last practice session are smaller than errors in the first practice session, and comparably hard to detect based on intrinsic feedback. Due to the smaller errors, the bandwidth for positive feedback became smaller. Accordingly, a performance, which might have been correctly evaluated as good in earlier blocks, might cause negative feedback in later blocks. This might explain the relatively large $\mathrm{FRN}_{\mathrm{peak}}$-amplitudes in late practice compared to early practice. If this were true, one would expect the $\mathrm{FRN}_{\mathrm{peak}}$-amplitudes to become smaller if the bandwidth were kept constant from the beginning to the end of the practice.

However, we want to add another rather speculative explanation here. Small $\mathrm{FRN}_{\mathrm{peak}}$-amplitudes in early practice might also result from some kind of informational overload. In general, high cognitive load has been shown to decrease the FRN-amplitude related to the $\mathrm{FRN}_{\mathrm{diff}}$ (Krigolson et al., 2015). Contrary to common research designs, in the present study, the participants had to process complex feedback information and evaluate three distinct critical movement elements. This might result in more insecurity and ambiguity in setting up a prediction to compare against the objective feedback value. From this perspective, an increase of the $\mathrm{FRN}_{\mathrm{peak}}$-amplitudes would not reflect a worse capability to predict the movement outcome, but an increased capability to set up a distinctive prediction (even if it is not a precise one) in this case. Over the course of practice and with improvement of performance, participants might become more confident in evaluating their own performance and thus, are more surprised when receiving negative feedback. This then results in larger amplitudes of the negative deflection in the time window of the FRN in the later practice session and could also explain the rather small valence-dependent differences in the early practice phase. Research of associations between confidence and neural feedback processing is rare. Using a time estimation task, Frömer and colleagues (Frömer et al., 2018) could not find a modulation of the FRN-amplitude ($\mathrm{FRN}_{\mathrm{peak}}$) by the confidence in one’s own outcome prediction. Further research is needed to scrutinize explanations for a setting-dependent increase of the $\mathrm{FRN}_{\mathrm{peak}}$-amplitudes in the later practice.

LFCP

Valence effects. With respect to the LFCP, we found more positive amplitudes after negative feedback, as expected (*H.LFCP.1*). According to Cockburn and Holroyd (2018), the LFCP might be associated with supervised learning processes (Caligiore et al., 2019), which might be of higher significance if the informational level of feedback is higher (e.g., information on direction and magnitude of errors) than binary information (e.g., correct vs. wrong). This effect confirms earlier findings (Krause et al., 2020), while augmenting it for the later practice session after extensive motor practice.

Practice-related changes. Contrary to the expectations, there were no practice-related changes in the LFCP (*H.LFCP.2*). We assume that the LFCP is associated with behavioral adaptations based on complex feedback (i.e., feedback containing information on direction and magnitude of the error) and could be ascribed to processes of supervised learning. Negative complex feedback is apparently processed equally with substantial reliance on supervised learning processes in both learning phases (early and late).

P300

Valence effects. The expectation about the P300 being more positive for positive feedback was also confirmed (*H.P300.1*). According to the context-updating hypothesis (Donchin and Coles, 1988), the P300 reflects the importance of the eliciting stimuli for the updating of internal models. As equal frequencies for events with positive and negative feedback were used, an expectancy effect can be ruled out here. Therefore, we assume that positive feedback is more significant and useful to update the internal model for this motor task and the respective feedback manipulation. It can further be assumed that negative feedback is more difficult to use in this task, as the corrective information is rather unreliable due to the ambiguity of the identity of the reversal being addressed. Higher positivity of the P300 after positive feedback has also been shown by Krause et al. (2020) in an identical experimental setting with one practice session and was also shown in other settings in the cognitive domain (Gu et al., 2011; Ma et al., 2013). Others found a more positive P300 component after negative feedback (Pfabigan et al., 2011; Yeung and Sanfey, 2004). The importance of feedback with a certain valence for the updating of internal models might depend on the task itself and the reliability of the feedback categories (positive vs. negative).

Practice-related changes. For the P300, a decreased amplitude in the later practice phase caused by a reduced need to update a well-established internal model after extensive practice was assumed. Against the Hypothesis *H.P300.2* and inconsistent with other studies in the cognitive domain (e.g., Bellebaum and Colosio, 2014; Bellebaum and Daum, 2008), there was a practice-related increase of positivity concerning both, positive and negative feedback. Thus, the updating process does not seem to be abundant in the later practice session, which is in line with further improvement throughout the later practice session. In line with the increasing P300 in one session of practice (Krause et al., 2020), the same argumentation might be true here for the more extensive practice phase: In the context of rather difficult and ambiguous feedback information, a valence-independent increase in the P300 might reflect better capabilities in the interpretation and usability of feedback information for the updating of the internal model.

Explorative analysis: Latency effects of the ERPs

With respect to the latencies of the ERPs, no homogeneous valence-dependent tendency was observed. Valence-dependent temporal occurrence of peaks differs between the components. Further, there were some practice-related changes in the latencies of the FRN and the LFCP, but not for the P300. Consistent with other research (e.g., Crowley et al., 2013; Zottoli and Grose-Fifer, 2012), the FRN peaked earlier after positive as compared to negative feedback in the early practice sessions. Rewards seemed to be processed faster than losses, which would indicate a sensitivity for positive outcomes. Moreover, it could be revealed that this valence-dependent difference in latencies was not observable in the late practice session, as the processing of positive feedback seems to be slowed down. In the later practice, the reward system might be attenuated. Smaller errors and a narrower bandwidth result in, that different boarders in the graphical feedback are closer to each other. Therefore, it might take longer to differentiate good and worse performance.

The P300 after negative feedback had longer latencies than the P300 after positive feedback in both phases of practice, which might be related to longer durations of stimulus categorization (Mecklinger and Ullsperger, 1993). A specific stimulus categorization might refer to the assignment of the error value to one of the three reversals. In sum, this would indicate that there is a lower sensitivity for negative feedback during the early practice phase (reflected in a longer FRN-related latency), and in more general, also more need for information processing in order to categorize the feedback (reflected in a longer P300-related latency).

Another point to discuss is the question in how far the components depend on each other, or whether they are based on independent processes. If the latencies for one component (e.g., the FRN evaluated at the FCz) show practice-related changes, and the same effects or a comparable temporal shift could be observed in a subsequent component (e.g., the LFCP, also evaluated at the FCz), one may assume that both components depend on each other in some way or another. But from what can be told from the present results, the latencies of the FRN remain the same (for negative feedback) or occur later (for positive feedback), but the latencies of the LFCP occur earlier after the extensive practice after positive and negative feedback. The earlier LFCP might reflect altered (e.g., faster) processes related to supervised learning, and the dissociation of FRN and LFCP latencies further underline that these components refer to different mechanisms of feedback-based learning (Cockburn and Holroyd, 2018). Because these effects have been analysed in an exploratory approach, future research should address these latency effects with a priori stated hypotheses.

Conclusion

In general, our hypotheses concerning the valence-dependence of distinct ERPs were confirmed. The FRN and the LFCP were more sensitive for negative feedback, while the P300 was more sensitive for positive feedback. Concerning practice-related changes in the ERPs, the present results replicated the findings of an earlier study for the P300 and LFCP (Krause et al., 2020), despite of the different number of practice sessions. Against our expectation, the FRN after negative feedback increased after the extensive practice phase. The increase of the FRN and the fact, that there was no change in LFCP amplitudes might reflect the importance of reinforcement learning (associated with the FRN) and supervised learning processing (associated with the LFCP) in the respective practice phase. This issue will be evaluated in further analyses of the predictive value for acute trial-to-trial changes (acquisition) and retention performance (learning) in the second part of this study (see Margraf et al., this issue).

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Author Contributions

Conceptualization: DK designed the study. Supervision: MW supervised the project. Investigation: DK and LM collected the research data. Data curation: DK and LM were responsible for the handling of the research data. Formal analysis: LM analysed the data, supported by DK. Visualization: LM prepared the figures. Writing – original draft: LM wrote the first draft of the manuscript. Writing – review & editing: LM, DK, and MW commented and revised the manuscript.

Chapter II

Valence-dependent neural correlates of augmented feedback processing in extensive motor sequence learning – Part II: Predictive value of event-related potentials for behavioral adaptation and learning

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Abstract

To examine the neural processing of valence-dependent augmented feedback, 38 students learned a sequential arm movement task with 192 trials in each of five practice sessions. The degree of motor automatization was tested under dual-task-conditions. EEG was recorded in the first and last practice session. This study is an additional analysis of the data from Margraf et al. [Margraf, L., Krause, D., & Weigelt, M. (this issue). Valence-dependent neural correlates of augmented feedback processing in extensive motor sequence learning – Part I: Practice-related changes of feedback processing.]. While Part I focused on changes in neural feedback processing after extensive motor practice, Part II examines coherences between neural feedback processing and short-term behavioral adaptations, as well as different dimensions of long-term learning (i.e., accuracy, consistency, and automaticity). It was found that more negative amplitudes of the FRN after negative feedback were predictive for goal-independent changes of behavior in the early practice phase, whereas more positive amplitudes of the LFCP after negative feedback were predictive for goal-directed behavioral adaptations (error reduction), independent from the practice phase. Unexpectedly, more positive amplitudes of the P300 after positive feedback were also a predictor for goal-directed behavioral adaptations. Concerning long-term learning and motor automatization, a positive correlation was found for the reduction of dual-task costs and LFCP-amplitudes after positive feedback in the early practice.

Introduction

Augmented feedback is an important tool to support motor learning, and is processed in dependence of its valence, as can be analysed via specific components of the event-related potential (see Part I: Margraf et al., this issue). Part I of this study scrutinized changes in valence-dependent neural processing (i.e., feedback-related negativity [FRN]; late fronto-central positivity [LFCP]; P300) of augmented feedback after extensive practice of a novel motor task. Part II addresses the predictive value of selected neural potentials for short-term behavioral adaptation, long-term learning, and motor automatization.

When examining the predictive value of distinct event-related potentials (ERPs), there are different aspects to be considered. First, there are different types of motor errors that are processed by different neural systems (e.g., Krigolson and Holroyd, 2006 & 2007a). Krigolson and Holroyd (2007a) differentiate “low-level” from “high-level” errors. Low-level errors are defined as discrepancies between the actual and the appropriate motor command in the respective situation. These relatively small discrepancies can be overcome rather easily. High-level errors indicate that the movement goal cannot be achieved and larger adaptations are required. While low-level errors are assumed to be processed in more posterior parts of the brain, the processing of high-level errors is supposed to be located in frontal areas. Related to the theory of reinforcement learning (Holroyd and Coles, 2002), those high-level errors activate the frontal monitoring system (including dorsal prefrontal cortex and anterior cingulate cortex, Jueptner et al., 1997) when the outcome is worse than expected, in order to adapt subsequent behavior (Krigolson and Holroyd, 2007b).

Based on this differentiation of errors (cf. Krigolson and Holroyd, 2007a), different types of behavioral adaptations should be considered. If the error information can be ascribed to a specific motor command, it can be adequately corrected in subsequent performance. This can be described as goal-directed behavioral adaptation. Whereas, if the error information cannot be ascribed to a specific component of the movement (for example, due to a lack of expertise), there will also be a change in the subsequent performance, but this change will be less directed (and will not necessarily correct the error). This can be described as goal-independent behavioral adaptation.

Since motor learning proceeds through distinct phases, there might be differences in neural error processing and correction in dependence of the learning phase. There are several models that differentiate and describe these distinct phases (Magill and Anderson, 2014; Masaki and Sommer, 2012). These models differ in the number of phases, in a range of two up to five phases. For example, Gentile (1972) as cited in Magill and Anderson (2014), proposes two learning phases (initial stage, later stages), whereas the model by Fitts and Posner (1967) describes three phases (cognitive stage, associative stage, autonomous stage). Doyon and Benali (2005) name five phases (fast learning, slow learning, consolidation, automatization, retention). The cognitive changes during the learning process are well described in the parallel neural network model (Hikosaka et al., 1999), as well as in the triarchic model by Chein and Schneider (2012). The discussion of all these models is beyond the scope of this article. As different as the models are in their details, there are some basic assumptions they have in common, which will be addressed in the following paragraph.

The early learning phases are characterized by exploration of different movement possibilities through trial-and-error by processing of outcome information (Magill and Anderson, 2014). There are numerous and large errors, the performance is highly variable, and consistency is lacking (Fitts and Posner, 1967; Magill and Anderson, 2014). But performance improves rather quickly (Doyon and Benali, 2005). Motor control heavily relies on cognitive processing and attention-dependent representations (Chein and Schneider, 2012; Hikosaka et al., 1999). In these early phases, the learner is not able to perform an additional attention demanding task, without showing a substantial decrease in performance in one or both tasks (i.e., high dual-task costs). In the later phases of learning, the rate of improvement decreases and the learning slows down (Doyon and Benali, 2005), and further gains spread out across several practice sessions (Masaki and Sommer, 2012). The movement pattern is refined and performance becomes more consistent (Magill and Anderson, 2014). In this phase, conscious control decreases and attention-independent representations are established, which enable a high degree of automatic motor control with a decreased involvement of attentional resources (Chein and Schneider, 2012; Hikosaka et al., 1999). In these later phases, the skill can be performed more automatically, which means that the learner is able to concurrently perform an attention-demanding task, without substantial decrease in performance in either of the tasks (i.e., low dual-task costs).

Automatization can be defined as a specific dimension of motor learning. To evaluate the degree of automaticity (i.e., reduction of attentional cognitive control), the measurement of dual-task costs and their practice-dependent changes is a suitable tool. Dual-task costs are defined as the performance decrement in a concurrent execution of the primary motor task and an attention-demanding secondary task (Abernethy et al., 2007). They can be quantified as difference in performance between single- and dual-task conditions. As attentional demands for motor control should be diminished in the later stages, dual-task costs should be substantially reduced in the secondary task.

Predictive Value of ERPs for Behavior

Several components of the human event-related brain potential are associated with feedback processing, and therefore, also with feedback-based learning (i.e. FRN, LFCP, P300). In Part I of this study, it was confirmed that these components are valence-dependent in the motor domain (Margraf et al., this issue) and are related to different neural learning processes (e.g., reinforcement learning, supervised learning; Caligiore et al., 2019; Chein and Schneider, 2012). These components might differentially predict short-term adaptations (i.e., trial-to-trial changes during practice) and long-term behavioral changes (i.e., learning, as measured in retention tests after sleep-related consolidation).

The long-term changes are especially interesting with regard to the predictive value of valence-dependent neural correlates of feedback processing in motor automatization.

Predictive Value on Short Term-Changes

Feedback-Related Negativity (FRN). In the context of feedback processing, a frontal component occurring about 250 ms after feedback-onset is discussed related to reward processing and reward prediction associated with reinforcement learning (Glimcher, 2011; Holroyd and Coles, 2002; Krigolson, 2018; for a review: San Martin, 2012). In the present experimental set-up (cf. Part I, Margraf et al., this issue) a deflection with more negative amplitudes for negative feedback compared to positive feedback in the respective time window was confirmed. Moreover, it was shown that there was a practice-related increase of negativity, but only in trials providing negative feedback. These results were interpreted according to the assumption that there are two independent, but overlapping processes resulting in two subcomponents of the FRN (e.g., Peterburs et al., 2016). The FRN_{diff} (or reward Positivity [RewP], Hajcak Proudfit, 2015) is quantified as valence-dependent difference wave between negative and positive outcomes, and is assumed to reflect reward-related processing. The FRN_{peak}, quantified as peak-to-peak measure from P2 to N2, is associated with errors in the prediction of a behavioral outcome (e.g., feedback information). As both subcomponents are associated with feedback processing, either as a signal of reward processing (FRN_{diff}) or as a signal of prediction errors (FRN_{peak}), it can be assumed that their amplitudes are indicators for subsequent behavioral adaptations. However, empirical findings are contradictory.

While some studies, using binary (qualitative) feedback, found a relationship between FRN-amplitudes and behavioral changes (FRN_{diff}: Cohen and Ranganath, 2007; Van der Helden et al., 2010; Yasuda et al., 2004), other studies, using more complex (quantitative) feedback, did not find this relationship (FRN_{diff}: Cockburn and Holroyd, 2018; FRN_{peak}: Arbel et al., 2013; Krause et al., 2020). Thus, feedback complexity seems to be a moderating factor with strong influence on the predictive value of the FRN-components for behavioral adaptations. With respect to the literature referred to above, the FRN is defined in the manner of the FRN_{diff}, except of Arbel et al. (2013) and Krause et al. (2020). Hence, it is not known if the FRN-subcomponents (FRN_{diff}; FRN_{peak}) differ related to their predictive value for behavioral changes.

LFCP. The late fronto-central positivity (LFCP, also FCP) is a rather rarely reported component, occurring about 350 – 550 ms above frontal areas, being more positive for negative feedback (Arbel et al., 2013; Cockburn and Holroyd, 2018; Krause et al., 2020). This was also confirmed in the present experimental set-up, with the extension that there were no practice-related changes after five sessions (cf. Part I, Margraf et al., this issue). As the LFCP is related to supervised learning processes (more complex information processing, with consideration of the discrepancy of the current outcome with respect to the goal), it is assumed, that the LFCP-amplitude is also an indicator for subsequent behavioral adaptations. As supervised learning integrates the desired outcome in relation to the current outcome, respective behavioral adaptations are expected to be more goal-directed and more effective in the reduction of errors than behavioral adaptations induced by reinforcement learning. Empirical findings are rare, but all found a positive association between the LFCP-amplitude and behavioral adaptations (time-estimation task: Cockburn and Holroyd, 2018; word-association task: Arbel et al., 2013; motor-control task: Krause et al., 2020). In the study of Krause et al. (2020), the task and experimental set-up was similar to the one, that was used in the present study (practice schedule with one instead of five practice sessions). They found that more positive amplitudes of the LFCP after negative feedback were associated with larger corrections of the previous error.

P300. The third component of interest is the P300, a positive deflection peaking about 300 ms up to 600 ms after feedback onset at central-parietal midline electrodes (Glazer et al., 2018; Nieuwenhuis et al., 2005; for a review: San Martin, 2012). In the present setting, larger positivity was found for positive feedback. Moreover, positivity increased over five sessions of extensive practice, independent from feedback valence (cf. Part I, Margraf et al., this issue). The P300 was mainly discussed in association with the context updating hypothesis (Donchin and Coles, 1988; Glazer et al.; 2018; San Martin, 2012). According to this hypothesis, the representation of the task (e.g., a motor sequence) is revised based on current information about behavioral consequences (e.g., feedback about movement outcome) to form a precise and detailed internal model. Depending on the feedback valence, the amplitude of the P300 might be an indicator for whether positive or negative feedback information is more useful to update the internal model in the respective setting. Higher amplitudes related to positive feedback are expected to predict behavioral stabilization, whereas higher amplitudes related to negative feedback are expected to predict corrective behavioral adaptations.

Again, the results are ambiguous: While some studies found amplitudes of the P300 associated with behavioral changes (gambling task: San Martin et al., 2013; probabilistic reversal-learning paradigm: Chase et al., 2010; neurofeedback-task: Zioga et al., 2019), others did not (motor learning: Krause et al., 2020; Van der Helden et al., 2010). But even with regard to the studies that found an association of the P300 and behavioral changes, results cannot be easily compared due to differences in tasks and practice conditions (e.g. feedback characteristics). Concerning the P300 and its association with short-term behavioral changes, it seems to be the case, that the task and especially the goal of the task modulate its predictive value.

Predictive Value on Long-Term Learning

Concerning long-term learning, we are not aware of a study that incorporated a consolidation phase in between two or more sessions (i.e., at least one night of sleep before retention). Therefore, the evaluation of the predictive value of feedback-related ERPs for long-term learning is an important research desideratum.

Predictive Value of the ERP-Components for Motor Automatization

A long-term objective of extensive motor practice is motor automatization. Recent evidence suggests that motor automatization processes heavily depend on the valence of augmented feedback (Agethen and Krause, 2016; Krause et al., 2018; Zobe et al., 2019). Motor automatization is characterized by a decrease of the involvement of attentional control processes (Fitts and Posner, 1967; Hikosaka et al., 1999, Poldrack et al., 2005). The attentional cognitive control network of the brain includes, besides others, the dorsal prefrontal cortex (dPFC) and the anterior cingulate cortex (ACC, Chein and Schneider, 2012; Jueptner et al., 1997; Lohse et al., 2014). In this context, it is to mention that the dorsal ACC (dACC) is assumed to be the generator of the FRN (Bellebaum and Daum, 2008; Hauser et al., 2014), with strong connections to the lateral prefrontal cortex, the parietal cortex, as well as premotor and supplementary motor areas. Several findings indicate the involvement of the dACC (beside others) in the modulation of attention, error detection, or activation related to working memory (Bush et al., 2000; Devinsky et al., 1995; Holroyd and Coles, 2002; Holroyd and Umemoto, 2016).

The FRN_{peak} reflects the disinhibition of the dACC (Peterburs et al., 2016), which might be a manifestation of activation of attentional control processes after error feedback (Botvinick et al., 2001; Botvinick et al., 2004), while the FRN_{diff} reflects reward processing, which promotes long-term potentiation of respective motor representations (Peterburs et al., 2016). Therefore, we expect that FRN amplitudes are correlated to motor automaticity and its practice-related change (i.e., automatization).

The link of the LFCP to attentional processes and automaticity is more ambiguous, as its neural source is not directly revealed so far. Moreover, the mechanism of supervised learning, to which the LFCP is associated to (Cockburn and Holroyd, 2018), is not discussed with regard to attention and automaticity. However, it can be assumed, that the supervised learning mechanism relies, at least to some extend, on attention-dependent processing of error information in relation to the desired outcome. Scrutinizing coherences of neural correlates of augmented feedback processing and motor automaticity, tested with a dual-task paradigm, is a research desideratum.

Hypotheses

This study focuses on valence-dependent components of the human event-related brain potential and their coherence with short-term behavioral changes during the practice of a motor task. Furthermore, we aim to examine the correlation between neural feedback processing and long-term learning (i.e., retention performance), with regard to increases in accuracy, consistency, and automatization (i.e., reduction of dual-task costs) of a motor skill. Therefore, a complex motor-sequence-learning task (i.e., an arm extension-flexion task using the right elbow joint), consisting of three movement reversals, was implemented in an ERP-study. The degree of automatization was tested using a dual-task paradigm, by adding a cognitive n-back-task.

Behavior-Related Hypotheses

According to the prioritization instruction for the motor task, dual-task costs (DTC) should be evident in the additional cognitive task (*H.DTC.1a*), but not in the motor task (*H.DTC.1b*). Dual-task costs should be reduced in the retention test (*H.DTC.2*). Deviations from the target movement pattern should be reduced, as signified by a smaller absolute error (*H.AE*), and performance should become more consistent, as indicated by a smaller variable error (*H.VE*).

Hypotheses on ERP-Components and Short-Term Behavioural Changes

We expect the following associations of neural processing and behavioral adaptation: More negative amplitudes of the FRN_{peak} should predict larger short-term behavioral adaptations (*H.FRN.1*). More positive amplitudes of the LFCP should predict larger short-term behavioural adaptations (*H.LFCP.1*). More positive amplitudes of the P300 after positive feedback should be associated with smaller short-term changes in behavior (*H.P300.1*). For all three components, the assumption that the coherence between these components and behavioural adaptations will change over time, were tested in an explorative fashion, without setting up directed hypotheses (*H.FRN.2*; *H.LFCP.2*; *H.P300.2*).

Hypotheses on ERP Components and Long-Term Learning

Concerning long-term learning, it was expected that higher valence-specific amplitudes of the FRN_{peak} (*H.FRN.3a*), of the FRN_{diff} (*H.FRN.3b*), of the LFCP (*H.LFCP.3*) and of the P300 (*H. P300.3*) predict higher retention performance of the motor task (i.e., a: movement accuracy and b: movement consistency). Moreover, higher amplitudes of the FRN_{peak} should induce lower amounts of automatization (*H.FRN.4a*), while higher amplitudes of the FRN_{diff} should induce higher amounts of automatization (*H.FRN.4b*). Further, it is assumed that higher amplitudes of the LFCP induce lower amounts of motor automatization (*H.LFCP.4*). Furthermore, it is hypothesized that higher amplitudes of the P300 after positive feedback predict the degree of motor automatization (*H.P300.4*).

Methods

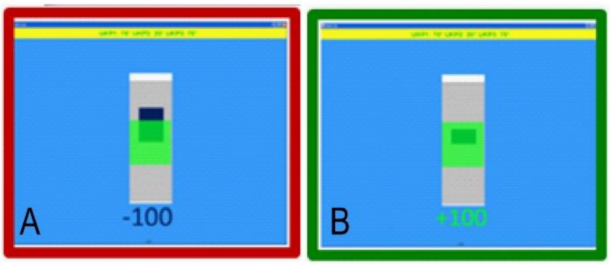
The present study is a complementary analysis of the data of Margraf et al. (Part I, this issue). The description of the experimental setting will therefore be focused on the relevant aspects for this analysis.

Participants. For data analysis, the final sample size consisted of 38 undergraduate university students (20 females; mean age = 20.87; age range = 18 – 26 years; 36 were right-handed as assessed with the German version of the Edinburgh Handedness Inventory, Büsch et al., 2010), of the originally 43 tested. All participants had normal or corrected to normal vision and no lesion of the upper limbs. The study was approved by the ethic committee from the German Psychological Society (DGPs).

Apparatus and task. In a pretest-posttest-design, participants practiced an extension-flexion-movement consisting of three movement reversals, executed with the right elbow with an adjustable underarm lever. The experimental set-up is explained in detail in Part I of this study (Figure 1, Margraf et al., this issue). The criterion task was an elbow flexion-extension sequence executed with the right arm. The movement consisted of three reversals at 70°, 20°, and 70°, measured outgoing from a defined position (0°) of the arm-lever device. Participants finished the sequence by crossing the neutral position without stopping. The task was to hit the reversals as precisely as possible and to keep the movement time below 1800 ms. The degree of automaticity of the criterion task was tested by adding a cognitive task in a dual-task test-design (explained in the procedure).

Figure 1

Feedback with a Performance Adaptive Bandwidth



Note: Feedback presented during the practice phase. The blue bar displays the magnitude and direction of the error for the reversal with the largest deviation. The green transparent bar displays the adaptive bandwidth based on the median of the preceeding block of 12 trials. Participants were told, the bandwidth would correspondend to the performance of a peer-sample. Fig. 1A displays an example of negative feedback, where the actual performance was outside of the bandwidth, and the participant lost 100 points. Fig. 2B displays an example for positive feedback, where the actual performance was within the bandwidth, and the participant earned 100 points.

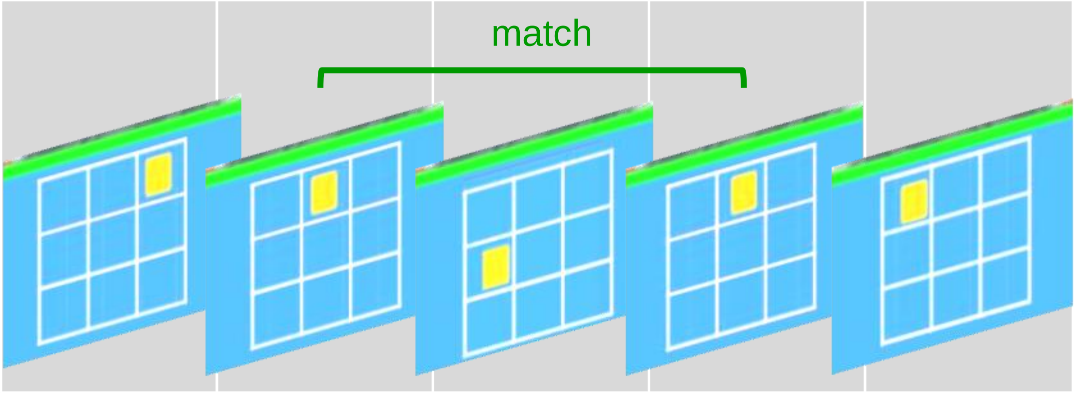
Procedure. The study consisted of seven experimental sessions of different lengths ranging from 30 up to 90 minutes. An overview of all experimental sessions can be found in Part I of this study (Figure 2, Margraf et al., this issue). The whole experiment was completed within 14 days, with at least 24 hours between two sessions. Learning was measured in three tests. T0: pre-acquisition test to get familiar with the test structure; T1: pre-test to measure performance before the practice phase; T2:

retention test to measure performance after the practice phase. During the 5 Practice sessions, feedback was given with a performance adaptive bandwidth (see Figure 1), leading to approximately 50% of trials in each valence category. For a detailed description of the practice phase and feedback characteristics, see Part I of this study (Margraf et al., this issue). The instruction of the tasks was provided via a presentation (PowerPoint, Microsoft) on the monitor and standardized verbal comments of the experimenter. This way of instruction was maintained for all sessions.

The first session was for formalities and initial acquisition. First, the criterion motor task was explained and practiced in five trials. Afterwards, the structure of the dual-task test was explained, which was the same for all three tests (T0, T1 and T2), and consisted of the motor task and an additional cognitive task. The tests began with six single-task trials of the cognitive task, followed by six single-trials of the motor task, 12 dual-task trials, another six single-trials of the motor task and finally, another six single-trials of the cognitive task. After the instruction of the test-structure the pre-acquisition test (T0) was executed.

Figure 2

Exemplary Section of the Cognitive n-Back Task



Note: Yellow rectangles were presented in a 3x3 matrix in randomized order. A match (position of the current rectangle is the same as the second last one) had to be marked by a left-hand key press. Here, the second and the fourth rectangle show a match. The other options (the first rectangle compared to the third and the third rectangle compared to the fifth) are no matches.

A visual-spatial n-back (2-back) task was used as additional cognitive task. Each trial started with the cue for preparation. After a countdown from three to one, followed by a fixation cross, yellow rectangles (9 per trial) were presented in a 3x3 matrix on a blue screen in randomized order (see Figure 2). The inter-stimulus interval alternated between 700 ms and 1000 ms, stimulus duration was 500 ms. The task was to respond to matches between the actual presented rectangle position and the second-last one with a left-hand key press. Errors were defined as omitted matches without a key press and key presses as response to non-matches. All inputs (correct and incorrect) were recorded. Participants received no augmented feedback information, whether their responses were correct or not.

Each trial of the motor task started with the request to bring the arm into the starting position. After 1500 ms, a red bar at the upper edge of the blue screen switched to green. This resembled the imperative signal for movement execution (start of the execution time window). Participants were informed that the aim was not to respond as soon as possible, but that the movement had to be finalized before the bar turned red again, indicating the end of the interval 3000 ms after the imperative signal. An acoustic signal marked the change of colours. During the execution time window, the motor task had to be executed within a movement-time window of 1800 ms. No feedback was presented during the test trials.

Each dual-task trial started with the n-back task on the screen, with a red bar at the upper edge. Like in the single-task condition, this bar switched to green after 1500 ms and the participant was allowed to start and finalize the motor execution until the bar turned red again after 3000 ms. While the motor task was executed, the n-back task continued, so both tasks had to be performed concurrently. During dual-task conditions, participants were instructed to prioritize the motor task and perform the cognitive task as accurate as possible, without impairment of the motor task.

The first session ended with a first short practice block of 36 trials of the motor task. From Trial 1 up to Trial 12, participants received feedback about the direction and magnitude of the deviations for each reversal, presented as blue bar graphs. For the remaining trials, they received only feedback for the reversal with the largest deviation, without information on the reversals identity (i.e., first, second or third reversal of the sequence).

The second session started with the pre-test (T1: dual-task test as described above). Afterwards, the first extensive practice started with 12 more trials of the motor task, without feedback (reference for the performance adaptive feedback), followed by four blocks of 48 trials with subsequent feedback after every trial. Feedback information was altered block-wise, as the bandwidth for positive feedback was set to the median performance of the respective last block of 12 trials. This performance adaptive bandwidth for positive feedback led to comparable frequencies for positive and negative feedback (cf. Part I, Margraf et al., this issue). Feedback was presented after the time window for movement execution was closed, which led to a feedback delay between 1000 ms and 2000 ms. Like in the end of the acquisition phase in Session 1, it was plotted as a blue bar graph, indicating the direction and magnitude of the reversal with the highest deviation. In addition, the bandwidth was presented as a transparent green bar, that overlaid the blue feedback bar (Figure 1). A detailed description can be found in the first part of this study (Margraf et al., this issue).

Session 3 up to Session 6 (Practice 2 – Practice 5) consisted of 12 trials without feedback, followed by 192 trials with feedback as described above. EEG was recorded in Practice 1 and Practice 5 (Session 1 and Session 6). In the last session, the retention test (T2) was conducted. This test was identical to the dual-task tests in Session 1 (pre-acquisition test) and Session 2 (pre-test).

EEG Recordings and Data Analysis. EEG recordings and analysis of the neural data was the same as in the first part of this study, for a detailed description see Part I, Margraf et al. (this issue). In the following, only additional analyses for coherences between behavioral and neural activation are described.

The analysis of coherences of behavioral data and event-related potentials was conducted according to Krause et al. (2020). The evaluation of trial-to-trial changes was based on two different types of behavioral adaptations. The change of the maximum absolute error (maxAE change) reflects a goal-directed behavioral adaptation. It was quantified as the largest of the three deviations of the concurrent reversals from the respective goal-value in absolute angular degrees. The change in the movement over all three reversals (reversal change) reflects a goal-independent adaptation of behavior. It was calculated as the mean absolute deviation of the concurrent three reversals from the respective goal-values in angular degrees. ERP amplitudes for each trial were calculated as z-values. This was done for each participant and for each session separately. Based on the individual median, the ERP amplitudes were labeled as low or high.

In order to evaluate the degree of motor automatization, the dual-task-tests of Sessions 1, 2, and 7 were analyzed. All trials that contained less or more than three reversals were excluded (4.17 % of a total of 1368 trials in the dual-task condition, 1.9 % of a total of 1368 trials in each of the both single-task conditions). All trials, in which the movement time of 1800 ms was exceeded, were kept, if they were executed within the maximum execution-time-window of 3000 ms.

For the cognitive task (n-back), the mean error per trial was calculated as the mean number of omitted responses to matches and responses to non-matches. For the movement task, the absolute error in angular degrees was calculated for each trial. The absolute differences between the actual and the target values were calculated for each movement reversal of the trial. The mean of this calculation was used as absolute error of this trial. The variable error was calculated for each of the three reversals as the standard deviation. Then, the mean variable error of the reversals was calculated. Dual-task costs were calculated as the difference between n-back-errors that were made in the single-task and dual-task condition.

With respect to movement automatization in relation to feedback processing, correlations between the reduction of dual-task costs and the neural activation were calculated separately for each ERP component (FRN_{peak}, FRN_{diff}, LFCP, P300) and for each of the examined practice sessions (Practice

1, Practice 5). The subcomponent FRN_{diff} was quantified as the difference between the valence-specific peaks after positive and negative feedback. Further, correlations between the reduction of movement errors (absolute error and variable error) and the neural activation were calculated separately for each ERP component (FRN_{peak}, FRN_{diff}, LFCP, P300) and for each examined practice session (Practice 1, Practice 5).

Statistical analyses were performed with SPSS (IBM Statistical Package for the Social Science). The alpha level was set to .05 for all analyses. Additionally, partial eta squared was calculated as effect size. All results are given as mean values and standard deviations.

For the behavioral data, a series of ANOVAs with repeated measures on *time* (T0, T1, T2) x *condition* (single-task, dual-task) were calculated for the absolute and variable error in the motor task as well as for the n-back error in the cognitive task. For coherences of ERP-amplitudes and behavior, ANOVAs with repeated measures on *amplitude* (low, high) x *valence* (positive, negative) x *session* (Practice 1, Practice 5) were calculated for the maxAE change and the reversal change, separately for the FRN and the LFCP, as well as for the P300. Follow-up analyses were conducted with paired *t*-tests. One-tailed tests based on directed hypotheses were labeled (t_1).

Results

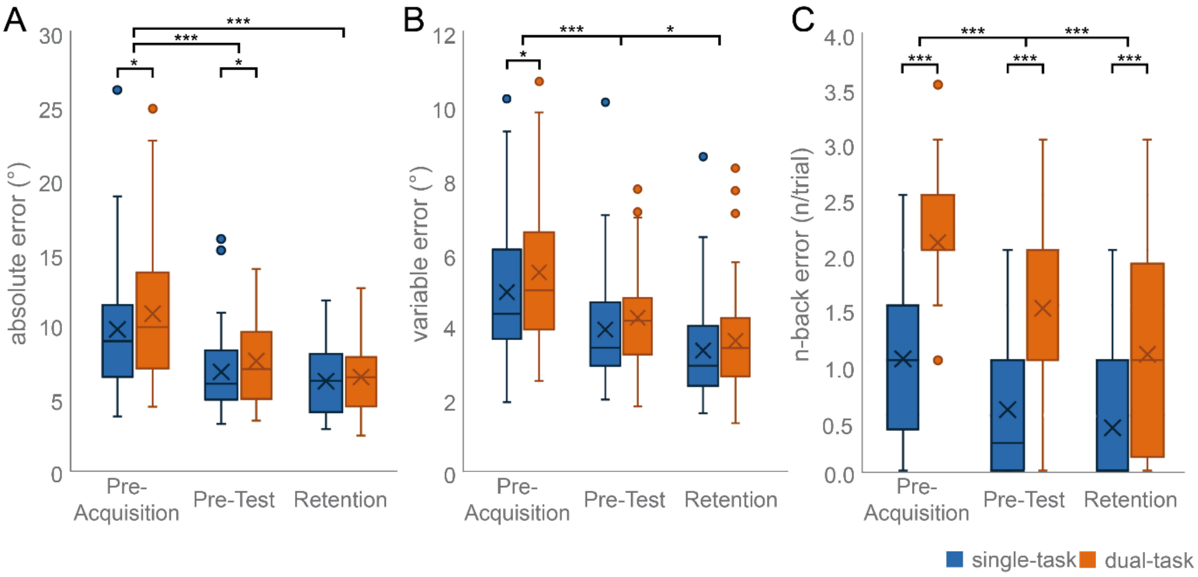
Behavioral Results

Retention

Absolute Error in the Motor Task. The 3 (*time*: T0, T1, T2) x 2 (*condition*: single-task, dual-task) ANOVA for the absolute error showed a main effect for *time*, $F(2,38) = 20.22$, $p < .001$, $\eta^2_p = .35$. Follow-up analyses reveal that participants were able to hit the reversals more accurate in the pre-test (M = 6.99; SD = ±2.60), $t(1,37) = 4.44$, $p < .001$, $d = 0.72$, and in the retention test (M = 6.13; SD = ±2.19), $t(1,37) = 5.21$, $p < .001$, $d = 0.84$, as compared to the pre-acquisition test (M = 10.08; SD = ±4.18). There was no significant difference between accuracy in the pre-test (M = 6.99; SD = ±2.60), as compared to the retention test (M = 6.13; SD = ±2.19), $t(1,37) = 1.68$, $p = .102$, $d = 0.27$. It was expected that deviations from the target movement pattern should be significantly reduced in the retention test. Hence, the hypothesis *H.AE* cannot be supported, as there was no further decrease of the absolute error in the main intervention phase after the initial 36 trials of practice (pre-test to retention). Further, the main effect for *condition*, $F(1,38) = 9.02$, $p = .005$, $\eta^2_p = .20$, was significant. Participants were able to hit the reversals more accurate in the single-task condition (M = 7.38; SD = ±2.16), as compared to the dual-task condition (M = 8.10; SD = ±2.23), $t(1,37) = 3.00$, $p = .005$, $d = 0.49$. As participants were instructed to prioritize the motor task, it was expected that there should be no difference in performances in the single-task and dual-task conditions related to the motor task. Therefore, the hypothesis *H.DTC.1b* cannot be supported, because participants were not able to focus mainly on the motor task, when there was an additional cognitive task. The interaction of *time* x *condition* was not significant, *F*(2,38) = 0.90, *p* = .412, η^2_p = .02. The results are displayed in Figure 3 (A). Therefore, further analyses on dual-task costs will focus on the cognitive task side.

Figure 3

Behavioral Results in the Motor Task and in the Cognitive Task



Note: Behavioral results for the single-task condition (blue) and the dual-task condition (orange) for the pre-acquisition test, the pre-test and the retention test. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box, for A: the absolute error in the motor task in angular degrees, B: the variable error in the motor task in angular degrees, and C: the n-back error in number of errors per trial for the cognitive task. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

Variable Error in the Motor Task. The 3 (*time*: T0, T1, T2) x 2 (*condition*: single-task, dual-task) ANOVA for the variable error revealed a main effect for *time*, *F*(2,38) = 16.26, *p* < .001, η^2_p = .31. Follow-up analyses reveal that participants were able to hit the reversals more consistent in the pre-test (*M* = 4.10; *SD* = ±1.30), as compared to the pre-acquisition test (*M* = 5.22; *SD* = ±1.74), *t*(1,37) = 3.63, *p* < .001, *d* = 0.59, and more consistent in the retention test (*M* = 3.51; *SD* = ±1.33), as compared to the pre-test (*M* = 4.10; *SD* = ±1.30), *t*(1,37) = 2.12, *p* = .041, *d* = 0.34. It was expected that the performance should be more consistent in the retention test. The hypothesis *H.VE* can be supported, as performance was significantly more consistent in the retention test compared to the pre-test. Also the main effect for *condition*, *F*(1,38) = 6.79, *p* = .013, η^2_p = .16, was significant. Participants hit the reversals more consistent in the single-task condition (*M* = 4.09; *SD* = ±0.96), as compared to the dual-task condition (*M* = 4.46; *SD* = ±1.20), *t*(1,37) = -2.61, *p* = .013, *d* = 0.42. The *time* x *condition* interaction failed to be significant, *F*(2,38) = 0.29, *p* = .749, η^2_p = .01. The results are displayed in Figure 3 (B).

Automatization

N-back error. The 3 (*time*: T0, T1, T2) x 2 (*condition*: single-task, dual-task) ANOVA for the n-back error showed a main effect for *time*, *F*(2,38) = 65.05, *p* < .001, η^2_p = .64. Participants were able to reduce the number of n-back-errors in the pre-test (T1: *M* = 1.21; *SD* = ±0.49), as compared to the pre-acquisition test (T0: *M* = 1.65; *SD* = ±0.49), and they were also able to reduce the number of n-back-errors in the retention test (T2: *M* = 0.93; *SD* = ±0.55), as compared to the pre-test (T1; *M* = 1.21; *SD* = ±0.49). Participants made more errors in the dual-task condition (*M* = 1.68; *SD* = ±0.49) than in the single-task condition (*M* = 0.85; *SD* = ±0.51), as shown by the main effect for *condition*, *F*(1,38) = 150.42, *p* < .001, η^2_p = .80. As assumed in the hypothesis *H.DTC.1a*, more errors were made in the dual-task condition. Further, the interaction of *time* x *condition* was significant, *F*(2,38) = 3.77, *p* = .028, η^2_p = .09. Follow-up analyses revealed that dual-task costs (difference between single- and dual-task condition) were lower in the retention test (T2: *M* = 0.64; *SD* = ±0.76) than in the pre-acquisition test (T0: *M* = 0.96; *SD* = ±0.59), t_1(1,37) = 1.95, *p* = .029, *d* = 0.33 and the pre-test (T1: *M* = 0.87; *SD* = ±0.60), t_1(1,37) = 1.86, *p* = .035, *d* = 0.30. It was expected that dual-task costs measured in the cognitive task should be reduced in the retention test, therefore, the hypothesis *H.DTC.2* can be supported. The results are displayed in Figure 3 (C).

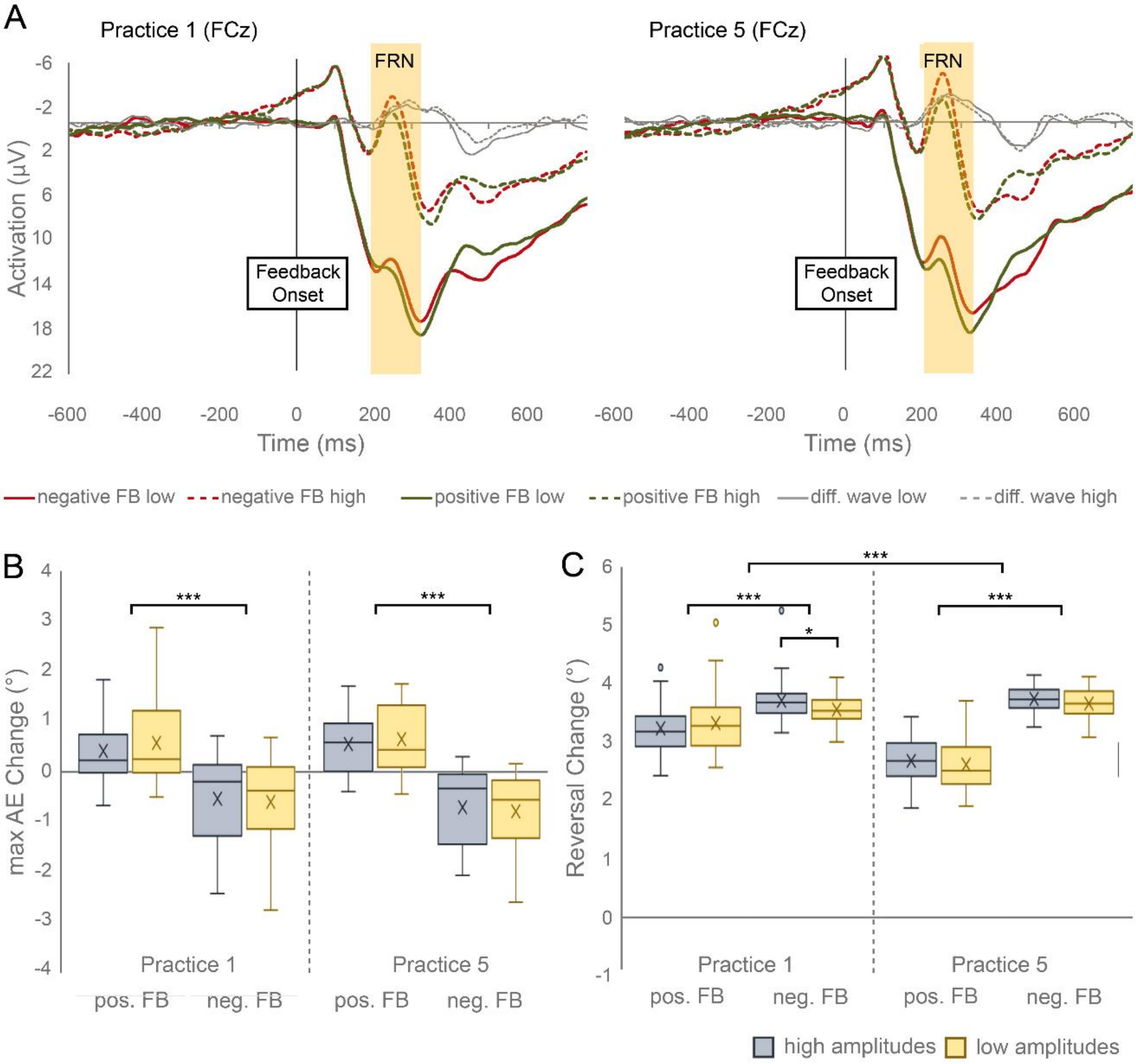
ERP-Components and Short-Term Behavioral Changes

FRN

MaxAE change. With regard to the FRN_{peak}, the 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) x 2 (*practice*: Practice 1, Practice 5) ANOVA for the maxAE change revealed a main effect for *valence*, *F*(1,38) = 45.71; *p* < .001; η^2_p = .55. Participants reduced the maxAE more after negative feedback (*M* = -0.68; *SD* = ±0.60), as compared to positive feedback (*M* = 0.52; *SD* = ±0.51). There were no significant effects for *practice*, *F*(1,38) = 0.64; *p* = .430; η^2_p = .02, and *amplitude*, *F*(1,38) = .40; *p* = .531; η^2_p = .01. The interaction of *valence* x *amplitude* just fell short of significance, *F*(1,38) = 3.61; *p* = .065; η^2_p = .09. None of the other interactions were significant (*practice* x *valence, F*[1,38] = 1.09; *p* = .303; η^2_p = .03; *practice* x *amplitude*, *F*[1,38] = 0.09; *p* = .762; η^2_p < .01; *practice* x *valence* x *amplitude, F*[1,38] = 0.06; *p* = .802; η^2_p < .01.). It was expected that more negative amplitudes of the FRN should predict larger behavioral adaptations. Therefore, the hypothesis *H.FRN.1* cannot be supported with respect to error correction. Further, the hypothesis *H.FRN.2* cannot be supported, as it was expected that there should be changes over the course of practice. The results are displayed in Figure 4 (A and B).

Figure 4

Coherences between ERPs and Behavioral Results for the FRN$_{peak}$



Note: A: ERP plots at the FCz electrode for the FRN$_{peak}$-amplitudes in microvolt, labeled as high (dashed lines) and low (solid lines) for negative feedback (red) and positive feedback (green) in Practice 1 (on the left side) and Practice 5 (on the right side). B: Changes of the maximum absolute error (in angular degrees) in dependence of FRN$_{peak}$-amplitudes labeled as high (more negative, yellow) and low (blue) for positive feedback (pos. FB) and negative feedback (neg. FB) in Practice 1 and Practice 5. C: Reversal changes (in angular degrees) in dependence of FRN$_{peak}$-amplitudes labeled as high (more negative, yellow) and low (blue) for positive feedback (pos. FB) and negative feedback (neg. FB) in Practice 1 and Practice 5. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

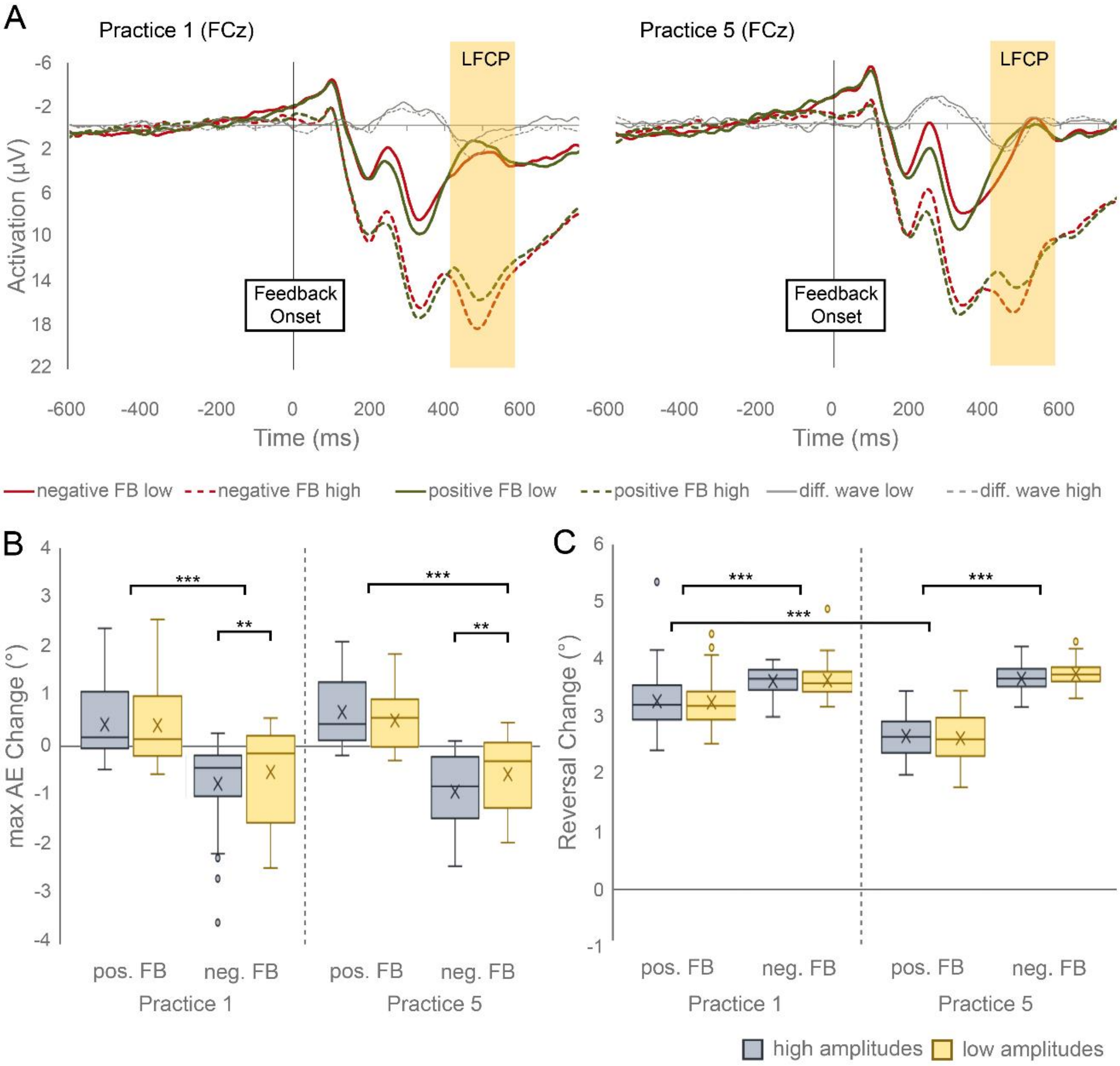
Reversal change. With respect to the FRN$_{peak}$, the 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) x 2 (*practice*: Practice 1, Practice 5) ANOVA for the reversal change revealed a main effect for *practice*, $F(1,38) = 112.58$; $p < .001$; $\eta^2_p = .75$. Reversal changes were smaller in Practice 5 ($M = 3.05$; $SD = \pm0.62$), as compared to Practice 1 ($M = 3.39$; $SD = \pm0.22$). Further, there was a main effect for *valence*, *F*(1,38) = 161.47; *p* < .001; η^2_p = .81. There were larger changes after negative feedback (*M* = 3.58; *SD* = ±0.07), as compared to positive feedback (*M* = 2.86; *SD* = ±0.40). The interaction of *session* x *valence*, *F*(1,38) = 91.41; *p* < .001; η^2_p = .71, was significant, as well as the interaction of *practice* x *valence* x *amplitude*, *F*(1,38) = 4.79; *p* = .035; η^2_p = .12. To identify these interactions, a 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) ANOVA was calculated for each practice. The interaction of *amplitude* x *valence* was significant in Practice 1, *F*(1,38) = 7.36; *p* = .010; η^2_p = .16, but not in Practice 5, *F*(1,38) = 0.03; *p* = .865; η^2_p < .01. Post-hoc *t*-Tests concerning Practice 1 revealed a significant difference between high and low amplitudes for negative feedback, t_1(1,38) = -1.87; *p* = .035, d = 0.29, but not for positive feedback, *t*(1,38) = 1.46; *p* = .154, d = 0.24. Larger reversal changes were associated with larger (more negative) amplitudes of the $\mathrm{FRN}_{\mathrm{peak}}$ after negative feedback (*M* = 3.64; *SD* = ±0.37), as compared to smaller amplitudes (*M* = 3.49; *SD* = ±0.25) in the early practice phase. There was no general main effect for *amplitude*, *F*(1,38) = 2.44; *p* = .127; η^2_p = .06, and no other interactions were significant (*practice* x *amplitude*, *F*[1,38] = 0.27; *p* = .607; η^2_p = .01; *valence* x *amplitude*, *F*[1,38] = 4.04; *p* = .052; η^2_p = .10). The expectation that larger FRN amplitudes were associated with larger behavioral adaptations (*H.FRN.1*) can be supported for goal-independent movement changes. As this effect was only found in the early practice, the hypothesis *H.FRN.2*, that states practice-related changes, can also be supported in this case. The results are displayed in Figure 4 (A and C).

LFCP

MaxAE change. With regard to the LFCP, the 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) x 2 (*practice*: Practice 1, Practice 5) ANOVA for the maxAE change revealed a main effect for *valence*, *F*(1,38) = 45.71; *p* < .001; η^2_p = .55. Negative feedback resulted in a reduction of the maxAE (*M* = -0.69; *SD* = ±0.61), in contrast to positive feedback (*M* = 0.52; *SD* = ±0.52). Also, the interaction of *valence* x *amplitude* was significant, *F*(1,38) = 13.55; *p* = .001; η^2_p = .27. Post-hoc *t*-Tests revealed a significant difference between low and high amplitudes of the LFCP after negative feedback, *t*(1,38) = -3.65; *p* = .001, *d* = 0.59, but not after positive feedback, *t*(1,38) = 1.37; *p* = .178, *d* = 0.22. The reduction of the maxAE was higher after negative feedback followed by high (more positive) amplitudes of the LFCP (*M* = -0.83; *SD* = ±0.67), as compared to low amplitudes (*M* = -0.54; *SD* = ±0.62). No other main effects (*practice*, *F*[1,38] = 0.62; *p* = .437; η^2_p = .02; *amplitude*, *F*[1,38] = 3.72; *p* = .062; η^2_p = .09) or interactions were significant (*practice* x *valence*, *F*[1,38] = 1.04; *p* = .316; η^2_p = .03; *practice* x *amplitude, F*[1,38] = 0.03; *p* = .856; η^2_p < .01; *practice* x *valence* x *amplitude*, *F*[1,38] = 1.32; *p* = .258; η^2_p = .03). It was expected that more positive amplitudes of the LFCP should predict larger behavioral adaptations. Therefore, the hypothesis *H.LFCP.1* can be supported with respect to error correction. The hypothesis *H.LFCP.2* cannot be supported, as it was expected that there should be changes over the course of practice, which was not the case. The results are displayed in Figure 5 (A and B).

Figure 5

Coherences between ERPs and Behavioral Results for the LFCP



Note: A: ERP plots at the FCz electrode for the LFCP-amplitudes in microvolt, labeled as high (dashed lines) and low (solid lines) for negative feedback (red) and positive feedback (green) in Practice 1 (on the left side) and Practice 5 (on the right side). B: Changes of the maximum absolute error (in angular degrees) in dependence of LFCP-amplitudes labeled as high (more positive, yellow) and low (blue) for positive feedback (pos. FB) and negative feedback (neg. FB) in Practice 1 and Practice 5. C: Reversal changes (in angular degrees) in dependence of LFCP-amplitudes labeled as high (more negative, yellow) and low (blue) for positive feedback (pos. FB) and negative feedback (neg. FB) in Practice 1 and Practice 5. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

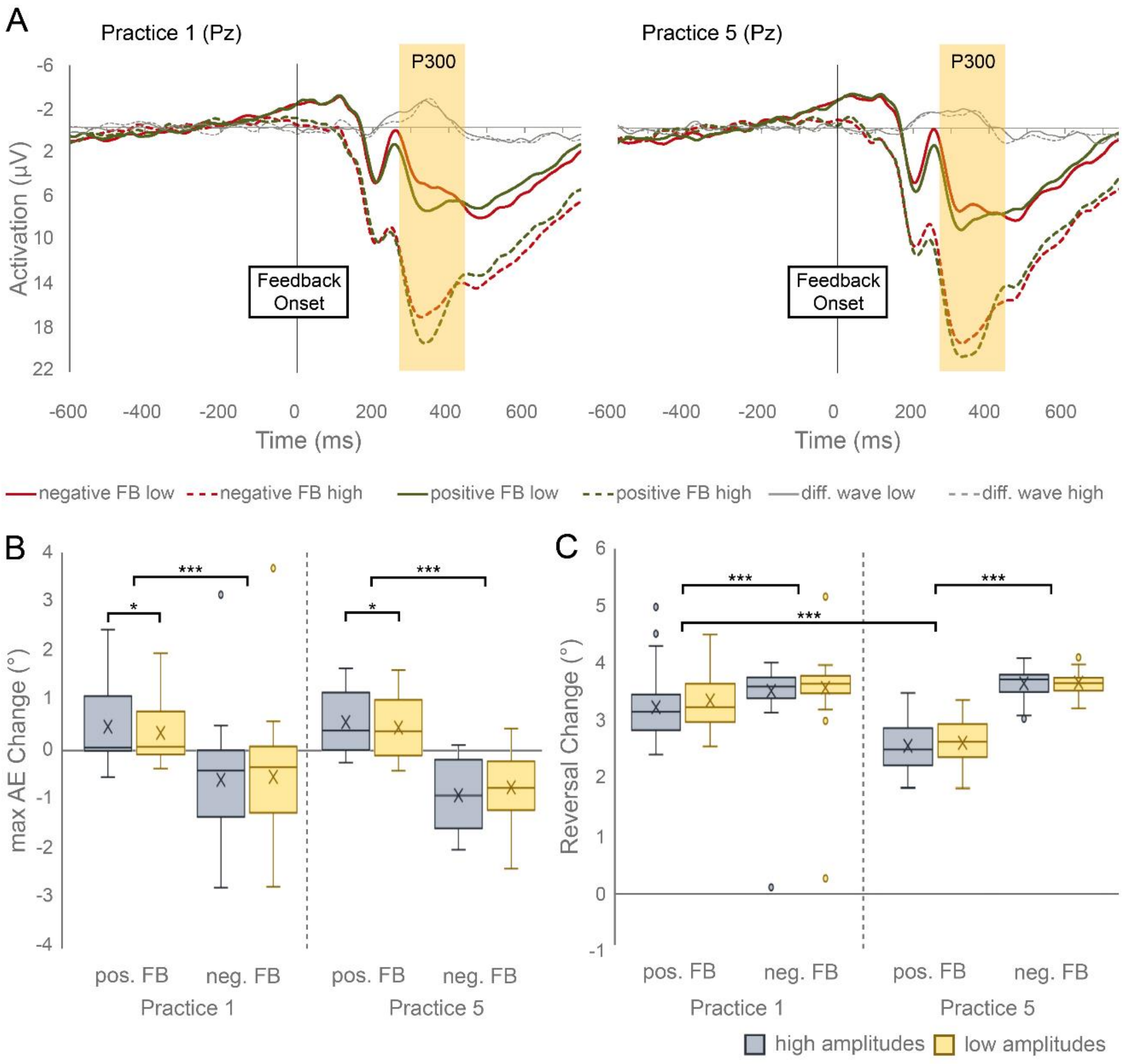
Reversal change. With regard to the LFCP, the 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) x 2 (*practice*: Practice 1, Practice 5) ANOVA for the reversal change revealed a main effect for *practice*, $F(1,38) = 114.55$; $p < .001$; $\eta^2_p = .76$. Reversal changes were smaller in Practice 5 ($M = 3.05$; $SD = \pm 0.62$), as compared to Practice 1 ($M = 3.39$; $SD = \pm 0.21$). Further, there was a main effect for *valence*, *F*(1,38) = 161.27; p < .001; η^2_p = .81. There were larger reversal changes after negative feedback (*M* = 3.58; *SD* = ±0.04), as compared to positive feedback (*M* = 2.86; *SD* = ±0.40). Further, there was a significant interaction of *practice* x *valence*, *F*(1,38) = 95.31; p < .001; η^2_p = .72. Post-hoc *t*-Tests revealed a significant difference between Practice 1 and Practice 5 for positive feedback, *t*(1,38) = 11.68; p < .001, *d* = 1.89, but not for negative feedback, *t*(1,38) = -0.49; p = .629, *d* = 0.10. The reversal changes after positive feedback were larger in Practice 1 (*M* = 3.20; *SD* = ±0.46) than in Practice 5 (*M* = 2.51; *SD* = ±0.37). There was no effect for *amplitude*, *F*(1,38) = 0.06; p = .809; η^2_p < .01, and no other interactions were significant (*practice* x *amplitude, F*[1,38] = 0.16; p = .693; η^2_p < .01; *valence* x *amplitude, F*[1,38] = 1.68; p = .202; η^2_p = .04; *practice* x *valence* x *amplitude*, *F*[1,38] = 0.45; p = .505; η^2_p = .01). The expectation that larger amplitudes of the LFCP were associated with larger behavioral adaptations (*H.LFCP.1*) cannot be supported for goal-independent movement changes. As there were no practice-related changes, the hypothesis *H.LFCP.2* cannot be supported either. The results are displayed in Figure 5 (A and C).

P300

MaxAE change. With regard to the P300, the 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) x 2 (*practice*: Practice 1, Practice 5) ANOVA for the maxAE change revealed a main effect for *valence*, *F*(1,38) = 36.88; p < .001; η^2_p = .50. Negative feedback resulted in a higher reduction of the maxAE (*M* = -0,64; *SD* = ±0.70), as compared to positive feedback (*M* = 0.52; *SD* = ±0.50). Further, the interaction of *valence* x *amplitude* was significant, *F*(1,38) = 5.50; p = .024; η^2_p = .13. Post-hoc *t*-Tests revealed a significant difference between low and high amplitudes only for positive feedback, *t*(1,38) = 2.52; p = .016, *d* = 0.41, but not for negative feedback, *t*(1,38) = -1.58; p = .123, *d* = 0.28. MaxAE change after positive feedback was larger after high P300-amplitudes (*M* = 0.58; *SD* = ±0.55), than after lower P300-amplitudes (*M* = 0.46; *SD* = ±0.50). No other main effects (*practice*, *F*[1,38] = 1.46; p = .234; η^2_p = .04; *amplitude*, *F*[1,38] = 0.02; p = .883; η^2_p < .01) or interactions were significant (*practice* x *valence*, *F*[1,38] = 1.64; p = .209; η^2_p = .04; *practice* x *amplitude, F*[1,38] = 0.51; p = .481; η^2_p = .01; *practice* x *valence* x *amplitude*, *F*[1,38]= 0.14 p = .712; η^2_p < .01).). It was expected that more positive P300-amplitudes after positive feedback should predict smaller behavioral adaptations. Against this expectation, more positive amplitudes were associated with larger behavioral adaptations with respect to error correction. So, the hypothesis *H.P300.1* cannot be supported. The hypothesis *H.P300.2* cannot be supported either, as it was expected that there should be changes over the course of practice, which was not the case. The results are displayed in Figure 6 (A and B).

Figure 6

Coherences between ERPs and Behavioral Results for the P300



Note: A: ERP plots at the Pz electrode for the P300-amplitudes in microvolt, labeled as high (dashed lines) and low (solid lines) for negative feedback (red) and positive feedback (green) in Practice 1 (on the left side) and Practice 5 (on the right side). B: Changes of the maximum absolute error (in angular degrees) in dependence of P300-amplitudes labeled as high (more positive, yellow) and low (blue) for positive feedback (pos. FB) and negative feedback (neg. FB) in Practice 1 and Practice 5. C: Reversal changes (in angular degrees) in dependence of P300-amplitudes labeled as high (more negative, yellow) and low (blue) for positive feedback (pos. FB) and negative feedback (neg. FB) in Practice 1 and Practice 5. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

Reversal change. With regard to the P300, the 2 (*amplitude*: high, low) x 2 (*valence*: positive, negative) x 2 (*practice*: Practice 1, Practice 5) ANOVA for the reversal change revealed a main effect for *practice*, $F(1,38) = 25.53$; $p < .001$; $\eta^2_p = .41$. Reversal changes were larger in Practice 1 ($M = 3.36$; $SD = \pm 0.42$), as compared to Practice 5 ($M = 3.05$; $SD = \pm 0.19$). Also, there was a main effect for *valence*, $F(1,38) = 96.18$; $p < .001$; $\eta^2_p = .72$. Reversal changes were larger after negative feedback ($M = 3.54$; $SD = \pm 0.29$), as compared to positive feedback ($M = 2.87$; $SD = \pm 0.38$). Analysis revealed a significant interaction of *practice* x *valence*, $F(1,38) = 44.63$; $p < .001$; $\eta^2_p = .55$. Post-hoc *t*-Tests revealed a significant difference between Practice 1 and Practice 5 for positive feedback, $t(1,38) = 9.91$; $p < .001$, $d = 1.61$, but not for negative feedback, $t(1,38) = -1.01$; $p = .319$, $d = 0.16$. The reversal changes after positive feedback were larger in Practice 1 ($M = 3.23$; $SD = \pm 0.50$), as compared to Practice 5 ($M = 2.51$; $SD = \pm 0.37$). There was no effect for *amplitude*, $F(1,38) = 3.20$; $p = .082$; $\eta^2_p = .08$, and no other interactions were significant (*practice* x *amplitude,* $F[1,38] = 0.59$; $p = .447$; $\eta^2_p = .02$; *valence* x *amplitude,* $F[1,38] = 0.49$; $p = .490$; $\eta^2_p = .01$; *practice* x *valence* x *amplitude*, $F[1,38] = 0.04$; $p = .836$; $\eta^2_p < .01$). The expectation that larger amplitudes of the P300 were associated with smaller behavioral adaptations (*H.P300.1*) cannot be supported for goal-independent movement changes, as there were no effects for *amplitude*. The hypothesis *H.P300.2* cannot be supported either, as there were no practice-related changes with respect to *amplitude* in association with behavioral adaptations. The results are displayed in Figure 6 (A and C).

Results on ERP-Components and Long-Term Learning

FRN

Higher FRN_{peak}-amplitudes were expected to be negatively correlated to the reduction of dual-task costs as frontal activity should hamper the process of motor automatization. But, there was no significant correlation between reduction of dual-task costs from the pre-test to the retention test and FRN_{peak}-amplitudes in Practice 1 (positive feedback: $r[38]) = .135$, $p = .418$; negative feedback: $r[38] = .170$, $p = .306$), nor in Practice 5 (positive feedback: $r[38] = .017$, $p = .318$; negative feedback: $r[38] = -.098$, $p = .556$). Therefore, the hypothesis *H.FRN.4a* cannot be not supported. Further, related to long-term learning, higher amplitudes of the FRN_{peak} were expected to predict higher retention performance in the motor task. But, no significant correlation between the reduction of the absolute error in the retention test, as compared to the pre-test and FRN_{peak}-amplitudes was found in Practice 1 (positive feedback: $r[38] = .012$, $p = .941$; negative feedback: $r[38] = .034$, $p = .837$), nor in Practice 5 (positive feedback: $r[38] = -.078$, $p = .642$; negative feedback: $r[38] = -.178$, $p = .284$). Also, no significant correlation with regard to the variable error was found in Practice 1 (positive feedback: $r[38] = -.193$, $p = .245$; negative feedback: $r[38] = -.206$, $p = .214$), nor in Practice 5 (positive feedback: $r[38] = -.166$, $p = .320$; negative feedback: $r[38] = -.096$, $p = .567$). The hypothesis *H.FRN.3a* cannot be supported.

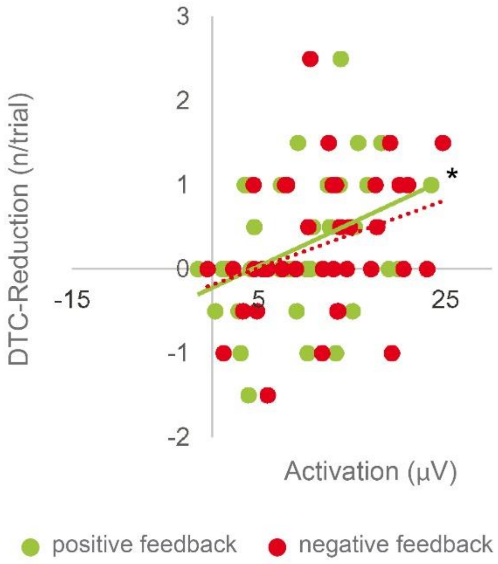
Higher amplitudes of the FRN_{diff} were expected to be correlated to the reduction of dual-task costs as reward processing should promote long-term potentiation of motor representations. But, there was no significant correlation between reduction of dual-task costs from the pre-test to the retention test and FRN$_{diff}$-amplitudes in Practice 1, *r*(38) = -.054, *p* = .373, nor in Practice 5, *r*(38) = .161, *p* = .167. The hypothesis *H.FRN.4b* cannot be supported. Related to long-term learning, higher amplitudes of the FRN$_{diff}$ were expected to predict higher retention performance in the motor task. No significant correlation between the reduction of the absolute error in the retention test and FRN$_{diff}$-amplitudes was found in Practice 1, *r*(38) = -.049, *p* = .386, nor in Practice 5, *r*(38) = .127, *p* = .224. Further, no significant correlation between the reduction of the variable error in the retention test and FRN$_{diff}$-amplitudes was found in Practice 1, *r*(38) = -.199, *p* = .115, nor in Practice 5, *r*(38) = .050, *p* = .382. Therefore, the hypothesis *H.FRN.3b* cannot be supported.

LFCP

For the LFCP it was predicted that higher amplitudes should induce lower amounts of automatization. The analysis revealed a significant correlation between the reduction of dual-task costs from the pre-test to retention test and LFCP-amplitudes for positive feedback in Practice 1; *r*(38) = .371, *p* = .022. Larger amplitudes (more positive) of the LFCP after positive feedback were associated with larger reductions of dual-task costs (Figure 7).

Figure 7

Significant Correlation of the LFCP Amplitude and DTC Reduction



Note: Reduction of dual-task costs in errors per trial in relation to LFCP amplitudes in micro voltage for positive (green) and negative (red) feedback. Significant results are marked, *p < 0.05, **p < 0.01, ***p < 0.001.

There was no significant correlation between reduction of dual-task costs and LFCP-amplitudes for negative feedback in Practice 1, *r*(38) = .319, *p* = .051, and Practice 5, *r*(38) = .163, *p* = .328, nor for positive feedback in Practice 5, *r*(38) = .156, *p* = .350. Hence, the hypothesis *H.LFCP.4* can only be partly supported. With respect to long-term learning, it was expected that higher amplitudes of the LFCP should predict higher retention performance. But, there was no significant correlation between the reduction of the absolute error from the pre-test to the retention test and LFCP-amplitudes in Practice 1 (positive feedback: *r*[38] = .258, *p* = .118; negative feedback: *r*[38] = .166, *p* = .321), nor in Practice 5 (positive feedback: *r*[38] = -.162, *p* = .330; negative feedback: *r*[38] = -.191, *p* = .252). Also, there was no significant correlation with regard to the variable error in Practice 1 (positive feedback: *r*[38] = -.039, *p* = .816; negative feedback: *r*[38] = -.026, *p* = .877), nor in Practice 5 (positive feedback: *r*[38] = -.041, *p* = .809; negative feedback: *r*[38] = -.061, *p* = .716). Therefore, the hypothesis *H.LFCP.3* cannot be supported.

P300

With respect to the P300, it was expected that higher amplitudes should predict higher reduction of dual-task costs (i.e., motor automatization). But there was no significant correlation between reduction of dual-task costs from the pre-test to the retention tests and P300-amplitudes in Practice 1 (positive feedback: *r*(38) = .124, *p* = .457; negative feedback: *r*(38) = .151, *p* = .366), nor in Practice 5 (positive feedback: *r*(38) = .054, *p* = .746; negative feedback: *r*(38) = .029, *p* = .861). Hence, the hypothesis *H.P300.4* cannot be supported. Further, it was expected that higher amplitudes of the P300 should predict higher performance in the motor task in relation to long-term learning. But, there were no significant correlations between smaller movement errors (absolute error) in the retention test compared to the pre-test and P300-amplitudes in Practice 1 (positive feedback: *r*[38] = -.047, *p* = .778; negative feedback: *r*[38] = -.067, *p* = .691), nor in Practice 5 (positive feedback: *r*[38] = -.210, *p* = .206; negative feedback: *r*[38] = -.290, *p* = .077). Also, there was no significant correlation with regard to the variable error in Practice 1 (positive feedback: *r*[38] = -.112, *p* = .504; negative feedback: *r*[38] = .014, *p* = .932), nor in Practice 5 (positive feedback: *r*[38] = .036, *p* = .829; negative feedback: *r*[38] = -.014, *p* = .932). Thus, the hypothesis *H.P300.3* cannot be supported.

Discussion

Behavioral Analysis of Motor Learning

Learning in terms of retention performance was mainly evident for the initial acquisition phase, but not for the extensive practice phase with regard to accuracy (absolute error). This development of learning is comparable to earlier studies with the same motor task (e.g., Agethen and Krause, 2016; Krause et al., 2018). With regard to the movement consistency (variable error), learning occurred for the initial acquisition phase, as well as for the extensive practice phase. This dissociation of movement accuracy (absolute error) and consistency (variable error) is also in line with earlier studies (Agethen and Krause, 2016; Krause et al., 2018; Winstein and Schmidt, 1990).

With regard to automaticity, a moderate effect on dual-task cost reductions was found for the secondary cognitive task, that can be interpreted as an increase in motor automatization (i.e., reduction of capacity-limited attentional control). Alternative explanations of reduced dual-task costs, like task switching or task integration (Manzey, 1988; Ruthruff et al., 2006), that might occur after multiple dual-task test blocks (Agethen and Krause, 2012), can be foreclosed as passive control groups in a similar experimental setting did show a null-effect on dual-task cost reductions (Agethen and Krause, 2016; Zobe et al., 2019).

The effect for dual-task cost reduction was moderate compared to earlier studies using the same task (Agethen and Krause, 2016; Krause et al., 2018). Differences in the feedback schedule account for the lower effect size. It had been expected, that 50% of feedback with negative valence was suboptimal for motor automatization (Krause et al., 2018), but necessary to scrutinize valence effects without the confounding of expectancy due to different frequencies of positive and negative feedback (Krigolson, 2018). Analyses of the dual-task costs on the motor-side did also reveal dual-task costs, albeit a prioritization of the motor task was instructed. But, as there was no significant changes in dual-task costs on the motor side, automatization-related analyses can be focused on the secondary task.

Predictive Value of the ERPs for Short-Term Behavioral Changes

Based on the functionality of the distinct ERPs (FRN, LFCP, P300) concerning valence-dependent feedback processing, some associations between certain characteristics of the components and subsequent behavioral adaptations were predicted. In the following, the results related to the predictive value of the ERPs for short-term behavioral changes are discussed.

For the FRN_{peak} as a signal of a prediction error (Glimcher, 2011), it was expected that more negative amplitudes were associated with larger behavioral adaptations. In line with this hypothesis, there were larger changes of the maximal absolute error (maxAE change) after negative feedback, which were also accompanied by higher FRN_{peak}-amplitudes, but this corrective behavior was not predicted by the amplitude variation of the FRN_{peak} within the valence categories. With respect to the overall alteration of the movement pattern (reversal change), larger changes were predicted by more negative amplitudes of the FRN_{peak} in the early practice phase. Feedback-based reduction of the maxAE can be interpreted as goal-directed, and adequate behavioral adaptation leading to error correction. Contrary, the reversal change, can be seen as a goal-independent behavioral adjustment. In the early practice phase, the internal model of the movement is assumed to be rather vague, and therefore, it might have been hard to identify the error that was made, based on the given feedback information. Please keep in mind here, that participants received feedback only about the reversal with the largest deviation, without information on the assignment to a specific reversal. As the FRN_{peak} is associated with reinforcement learning processes (Glimcher, 2011; Holroyd and Coles, 2002), mainly based on qualitative feedback information (such as 'hit' or 'miss'), it seems reasonable that the predictive value of the FRN_{peak} is more likely reflected in a goal-independent variable like the reversal change. Therefore, learning processes based on the FRN_{peak} may rather follow a trial-and-error strategy, which in turn should be more present in the earlier practice phase, caused by a rather vague internal model of the movement pattern.

This finding is difficult to integrate in the existing research. The studies that found a predictive value of the FRN-amplitude for behavioral changes (e.g., Cohen and Ranganath, 2007; Van der Helden et al., 2010, Yasuda et al., 2004) were based on qualitative feedback information and further, quantified the FRN in the manner of the FRN_{diff}. Those studies that were comparable, because they used quantitative feedback information did not find a predictive value for both, the FRN_{diff} (e.g., Cockburn and Holroyd, 2018) and the FRN_{peak} (e.g., Arbel et al., 2013; Krause et al., 2020).

Remarkably, the reversal change as goal-independent behavioral adaptation after positive feedback was significantly lower than after negative feedback in the later practice, whereas it was comparable after positive and negative feedback in the early practice. This effect is in line with the higher valence-dependent amplitude in the time window of the FRN_{peak} in the late practice session (cf., Margraf et al., this issue). It seems that the error information that is contained in positive feedback trials, due to the transparency of the error bandwidth in the visual feedback display, is processed like negative feedback in the early practice. In this regard, it remains to be solved why the FRN_{peak}-amplitude after positive feedback does not predict the reversal change. The use of error-information that is contained in positive feedback might be more inhomogeneous on an inter-individual level. In contrast to negative feedback, some participants might not show a high variance of the FRN_{peak}-amplitude after positive feedback events. Moreover, the FRN_{peak}-amplitude might be less directly related to behavioural consequences when conflicting information (i.e., qualitative positive feedback) is processed in addition to the quantitative error information. In other words, the FRN_{peak} might occur as the error is initially processed, but does not necessarily lead to behavioural consequences, as more complex integrative information processing overrules the error signal of the FRN_{peak}-related process. In this perspective, further research with a more integrative analysis of ERP components might reveal more insight.

Another point, that should be emphasized, is the fact, that we made a distinction in the kind of behavioral adaptations (i.e., goal-directed [error correction], goal-independent [reversal change]).

With exception of Krause et al. (2020), no other study made this distinction. Although their experimental setting was comparable to the one in the present study, Krause et al. (2020) did not find this relationship of the $\mathrm{FRN}_{\mathrm{peak}}$ and goal-independent behavioral changes. A possible explanation might be the number of practice sessions, which was one session versus five sessions. One might assume, that multiple practice sessions lead to a phase of trial-and-error to get familiar with different movement patterns and possibilities. The limitation to one session of practice might force to focus directly on identifying and correcting larger errors.

Goal-directed reduction of errors should be based mainly on supervised learning processes, which takes the goal movement pattern into account, in order to correct the error, and therefore may rather be reflected in the LFCP (Cockburn and Holroyd, 2018; Krause et al., 2020). Hence, more positive amplitudes of the LFCP after negative feedback were expected to be associated with subsequent behavioral adaptations. This expectation was confirmed, as changes of the maximal error were significantly predicted by higher LFCP-amplitudes after negative feedback, independent from the practice phase. Negative feedback serving complex feedback information, seems to activate attentional processes, leading to the error identification in order to correct it in the next trial. Although these results are in line with previous findings, it should be mentioned that results are limited and not entirely comparable with respect to the type of task (time-estimation task: Cockburn and Holroyd, 2018; word-association task: Arbel et al., 2013), except for one study using a motor-task, similar to the actual one (Krause et al, 2020). But all studies integrated quantitative feedback information.

In this (replicated finding of Krause et al., 2020) and other feedback settings (San Martin, 2012), the P300 is more positive after positive feedback and is mainly discussed in association with updating of the internal model (Donchin and Coles, 1988). As positive feedback should trigger the maintenance of previous behavior, we expected smaller changes of the movement pattern to be predicted by more positive amplitudes of the P300 after positive feedback. Against our expectation, we found more positive amplitudes of the P300 after positive feedback to be associated with larger error corrections. One possible but vague explanation refers to the feedback ambiguity in the present experiment, in which quantitative error information was also transported with positive feedback and assignment to the specific reversal was ambiguous. In this context, higher amplitudes of the P300 might reflect the result of successful identification of the necessary behavioural consequence to correct the error that was made, in order to maintain the rest of the previous movement pattern. Other possible explanations might take into account motivational or self-evaluating aspects of the participants. Arousal is moderated by feedback valence in a u-shaped fashion, where both, negative and positive feedback might increase arousal (Kluger et al., 1994). According to this view, the higher arousal might in turn increase performance, but these are only vague suspicions.

It is difficult to classify the present results concerning the P300. In general, there seem to be many factors, like the task characteristics, modulating the predictive value of the P300 for behavioral changes. At this point, it is reasonable to classify the present results only in the motor domain. But two studies could not find an association of P300 amplitudes and behavioral adaptations (Krause et al., 2020; Van der Helden et al., 2010).

With regard to short-term behavioral changes no clear indication of the predictive values of the ERPs can be made. Beside feedback complexity (qualitative versus quantitative) and the type of behavioral change (goal-directed versus goal-independent), the number of practice sessions seems to be another moderating variable influencing the predictive value of ERPs for short-term behavioral changes.

ERP-Components and Long-Term Learning

In addition to the influence of the selected components in short-term behavioral adaptations, distinct associations between different characteristics of the ERPs (FRN_{peak}, FRN_{diff}, LFCP, P300) and long-term learning, i.e., increase of accuracy, consistency and motor automatization were assumed. With respect to long-term learning as more accurate retention performance in the motor task, we could not verify any correlation and none of the hypotheses were confirmed. According to its origin in a neural substrate, that is described to an attentional control network (Hauser et al., 2014), it was expected that FRN_{peak}-amplitudes are related to the reduction of dual-task costs (i.e., automatization). However, no association between FRN_{peak}-amplitudes and reduction of dual-task costs was observed. The identification of an error reflected in the FRN_{peak} might be a precondition, but not a constraint for subsequent attentional control processes leading to behavioral corrections.

More complex, and therefore more attention-related error processing, might rather be reflected in the LFCP. Similar to the FRN_{peak}, also higher amplitudes of the LFCP were expected to result in a lower reduction of dual-task costs. Here, a significant correlation between LFCP amplitudes and reduction of dual-task costs was observed, but only concerning the early practice phase, and surprisingly with regard to positive feedback. The correlation related to negative feedback just fell short of significance. An explanation might be found in the transparency of the bandwidth, and therefore the error-information transported with positive feedback. In the early practice, deviations from the reversals were expected to be larger compared to the later practice. It seems to be the case, that those participants, that used any error-information for movement correction independent from feedback-valence in the early phase of practice, had an advantage with respect to motor automatization (reduction of dual-task costs). In an integrated discussion of both components (FRN_{peak} and LFCP), the FRN_{peak} might be interpreted as a ‘simple’ signal, indicating that there was a mismatch of the desired and actual outcome. Whereas the LFCP seems to be decisive in how this error signal is processed. Based on the theoretical approach of parallel neural networks (Hikosaka et al., 1999), we explain the present results as follows: A substantial error-correction in the early practice based on any kind of error-information supports a fast development of a stable movement representation in a spatial code. This, in turn, facilitates the development of the representation in a motor code, as the latter representation in the slow-learning motor system develops based on consistent input from the fast-learning spatial system (Hikosaka et al., 1999; Krause et al., 2014). We expect that those subjects, who were able to establish a stable representation early in practice, were also able to reduce attentional demands quite soon in the subsequent practice phase. Now, one could question, where this individual difference in the neural feedback processing relies on. This could be a topic for subsequent research in the present experimental setting. According to Krause et al. (2014), genetic variations in the dopaminergic metabolism might moderate interindividual differences in automatization capability. These genetic variations also moderate valence-dependent feedback processing (e.g., Mueller et al., 2014). To finish this chapter, it is to mention, that to our knowledge, there are no further results concerning ERP amplitudes in association to the degree of motor automatization. Research on this topic is a desideratum.

Conclusion of Both Parts of the Study

In conclusion, it should be noted, that single-trial analyses with emphasis of individual amplitudes of distinct ERPs reveal deeper insights in neural feedback processing compared to classical averaging techniques. While expectations concerning the sensitivity of distinct ERPs for feedback valence could be confirmed, it was also revealed that there are practice-related changes in error processing and that ERPs in general are predictive for short- as well as long-term behavioural changes. However, some results with respect to practice-related changes and the predictive value of neural processing for behavioral adaptations differed from what was expected. Although some ideas to explain these results were presented, further research is needed to clarify the influence of augmented feedback on neural feedback processing, especially in the motor learning domain.

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Author Contributions

Conceptualization: DK designed the study. Supervision: MW supervised the project. Investigation: DK and LM collected the research data. Data curation: DK and LM were responsible for the handling of the research data. Formal analysis: LM analysed the data, supported by DK. Visualization: LM prepared the figures. Writing – original draft: LM wrote the first draft of the manuscript. Writing – review & editing: LM, DK, and MW commented and revised the manuscript.

Supplements Chapter II

Calculation of DTC-reduction

In the current study, the reduction of dual-task costs was based on all three tests (pre-acquisition-test, pre-test, and retention test) (Margraf et al., 2022b; Part II, Chapter II). However, in previous studies that examine the impact of valence-dependent augmented feedback on motor automatization from the behavioral side (e.g., Agethen & Krause, 2016; Zobe et al., 2019) in the same experimental setting, the analysis of the reduction of dual-task costs was only analysed from the pre-test to the retention test. To establish comparability, the current data were also analysed retrospectively without the pre-acquisition-test.

Related to the absolute error in the motor task, the 2 (*time*: T1, T2) x 2 (*condition*: single-task, dual-task) ANOVA revealed no main effects of *time*, $F(2,38) = 2.82$, $p = .102$, $\eta^2_p = .07$, and of *condition*, $F(1,38) = 3.77$, $p = .060$, $\eta^2_p = .09$. Further, the interaction of *time* and *condition* failed to be significant, $F(2,38) = 1.34$, $p = .254$, $\eta^2_p = .04$. Related to the variable error in the motor task, the 2 (*time*: T1, T2) x 2 (*condition*: single-task, dual-task) ANOVA revealed a main effect of *time*, $F(1,38) = 4.41$, $p = .041$, $\eta^2_p = .11$. Follow-up analyses reveal that participants were able to hit the reversals more consistent in the retention test ($M = 3.51$; $SD = \pm 1.33$) as compared with the pre-test ($M = 4.10$; $SD = \pm 1.30$), $t(1,37) = 2.12$, $p = .020$, $d = 0.34$.

Related to the n-back task, the 2 (*time*: T1, T2) x 2 (*condition*: single-task, dual-task) ANOVA revealed a main effect of *time*, $F(2,38) = 21.02$, $p < .001$, $\eta^2_p = .36$, and of *condition*, $F(1,38) = 86.96$, $p < .001$, $\eta^2_p = .70$. Follow-up analyses revealed that participants made more n-back errors in the pre-test ($M = 1.21$; $SD = \pm 0.49$) as compared with the retention test ($M = 0.93$; $SD = \pm 0.55$), $t(1,37) = 4.59$, $p < .001$, $d = 0.74$, and participants made more errors in the dual-task condition ($M = 1.68$; $SD = \pm 0.49$) as compared with the single-task condition ($M = 0.85$; $SD = \pm 0.51$), $t(1,37) = -12.27$, $p < .001$, $d = -1.99$. Further the interaction of *time* and *condition* was significant, $F(2,38) = 4.86$, $p = .034$, $\eta^2_p = .12$. Follow-up analyses revealed that the difference between single-task and dual-task performance was significantly smaller in the retention test ($M = 0.64$; $SD = \pm 0.76$) as compared with the pre-test ($M = 0.87$; $SD = \pm 0.60$), $t(1,37) = 1.86$, $p = .035$, $d = 0.30$. Participant were able to reduce dual-task-costs from the pre-test to the retention test ($M = 0.28$; $SD = \pm 0.83$).

Predictive Value of ERPs for Correct Behavioral Adaptations

The variable for estimating goal-directed changes (maxAE change) was quantified as difference between the maximum absolute error of one trial (the reversal with the largest deviation from the goal-value out of the three reversals in one trial) and the maximum absolute error of the following trial (cf., Margraf et al., 2022b; Part II, Chapter II). Based on a comment during the peer-review process of another publication (Margraf et al., 2023; Part II, Chapter III) that suggested an alternative analysis, the way to quantify goal-directed changes was revised. A goal-directed change would be a behavioral adaptation which purposefully adjusts behavior, for example correct an error that was indicated by augmented feedback. Related to the current study, this would mean that the maximum error was successfully identified and corrected in the next trial. Based on the primary quantification described above, this cannot be investigated, because the reversal with the largest deviation in one trial does not have to be the same as in the next trial. This was not considered in the primary calculation.

To deal with this issue, the quantification of the goal-directed change was adapted (cf. Margraf et al., 2023; Part II, Chapter III). The goal-directed change was based on the difference of the reversal with the largest deviation from the goal-value (identified as maximum absolute error) in one trial and the deviation of that reversal in the following trial (even if it was not the maximum absolute error in that trial). The trials were then labelled in correct, which means a decrease of the deviation, or incorrect, which means an increase of the deviation. Related to this new calculation, it should be noted that the number of trials in both conditions (correct, incorrect) are no longer necessarily equal. Although this could have an impact on the neural components, this just seems to be the more appropriate way to evaluate goal-directed changes.

The adapted quantification was only applied to the analysis of frontal theta-band activity (Margraf et al., 2023; Part II, Chapter III) but it seems appropriate at this point to also examine the ERPs (which were based on the primary quantification) once again based on the adapted quantification. For the FRN the 2 (*time*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA revealed no significant effect of *correctness*, $F(1,36) = 0.98$, $p = .330$, $\eta^2_p = .03$, and none of the interactions including this factor was significant. Related to the LFCP the 2 (*time*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA also revealed no significant effect of *correctness*, $F(1,36) = 3.29$, $p = .078$, $\eta^2_p = .08$, and none of the interactions including this factor was significant. With respect to the P300 the 2 (*time*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA revealed a main effect of *correctness*, $F(1,36) = 17.42$, $p < .001$, $\eta^2_p = .33$. Amplitudes of the P300 were larger preceding incorrect changes of the maximum error ($M = 14.49$; $SD = \pm 5.02$) as compared with correct changes of the maximum error ($M = 13.80$; $SD = \pm 5.38$), independent from feedback valence and practice phase. None of the interactions including the factor *correctness* were significant.

Correlation Analysis of the LFCP and the Degree of Motor Automatization

Correlation analysis of the ERPs and the degree of motor automatization revealed a positive correlation between LFCP-amplitudes after positive feedback and the reduction of dual-task costs ($r = .37$; $p = .022$) in the first practice session. However, the correlation with respect to LFCP-amplitudes after negative feedback are just out of significance (*r* = .32; *p* = .051). Unfortunately, it was missed to check whether the correlation between LFCP-amplitudes and DTC reduction was independent of feedback valence. The retrospective analysis revealed a significant correlation between LFCP-amplitudes independent from feedback valence and the reduction of DTC (*r* = .35; *p* = .029) in the first practice session.

Chapter III

Frontal theta reveals further information about neural valence-dependent processing of augmented feedback in extensive motor practice – a secondary analysis

Citation of publication

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Abstract

Supplementing an earlier analysis of event-related potentials in extensive motor learning (Margraf et al., 2022a, b), frontal theta-band activity (4-8 Hz) was scrutinized. Thirty-seven participants learned a sequential arm-movement with 192 trials in each of five practice sessions. Feedback, based on a performance adaptive bandwidth, was given after every trial. EEG was recorded in the first and last practice session. The degree of motor automatization was tested under dual-task conditions in a pretest-posttest-design. Quantitative error-information was transported in both feedback conditions (positive, negative). Frontal theta activity was discussed as a general signal that cognitive control is needed, and therefore, was expected to be higher after negative feedback. Extensive motor practice promotes automatization and therefore, decreased frontal theta activity was expected in the later practice. Further, it was expected that frontal theta was predictive for subsequent behavioral adaptations, and the amount of motor automatization. As the results show, induced frontal theta power was higher after negative feedback and decreased after five sessions of practice. Moreover, induced theta activity was predictive for error correction, and therefore, an indicator whether the recruited cognitive resources successfully induced behavioral adaptations. It remains to be solved why these effects, that fit well with the theoretical assumptions, were only revealed by the induced part of frontal theta activity. Further, the amount of theta activity during practice was not predictive for the degree of motor automatization. It seems that there might be a dissociation between attentional resources associated to feedback processing and attentional resources associated to motor control.

Introduction

Motor skill learning accompanies humans throughout their lifespan, whether in sports (e.g., learning a new technique), in rehabilitation (e.g., after injury or stroke), or in daily life (e.g., handling a new device). Motor skill learning develops over distinct phases, which are described by several models (e.g., Fitts & Posner, 1967; Doyon & Benali, 2005; Magill & Anderson, 2014). In all these models, early phases are characterized by a larger amount and a larger magnitude of errors, high variability, and low consistency in movement performance, while in later phases, the performance becomes more accurate and consistent with a smaller amount and a smaller magnitude of errors. According to the *Model of Parallel Neural Networks* (Hikosaka et al., 1999), motor control relies heavily on cognitive and attention-dependent processing in the early phase of practice. During the learning progress the representation of the task is established and refined, so that in the later practice phases attention-dependent processes decrease and a higher degree of automatic control is implemented.

Motor automatization is important to enable complex movement control and a stable performance (e.g., in competitive sports), as it allows a secondary attention-demanding task to be performed without (or with only little) impairment of motor execution. From the behavioral side, this process can be evaluated by measuring dual-task costs (DTC, defined as the difference between single-task and dual-task performance related to the concurrent cognitive task) and their practice-dependent changes (Abernethy et al., 2007). From the neurophysiological side, the learning process is accompanied by a shift of activated brain regions from (among others) the dorsal prefrontal cortex (PFC) and the anterior cingulate cortex (ACC), both belonging to the cognitive control network, in the early practice (Jueptner et al., 1997; Lohse et al., 2014) to caudal-ventral (sensorimotor) areas of the striatum in the later practice (Grafton et al., 1995, Jueptner et al., 1997).

In this context, feedback plays an essential role in motor skill learning. In general, there is a distinction between two types of feedback: Task-intrinsic and augmented feedback (e.g., Magill & Anderson, 2014). Task-intrinsic feedback relates to the information that naturally arises from the sensory consequences of the movement execution itself (e.g., visual information of a ball's flight; kinaesthetic information on changes in muscle tension). Augmented feedback is defined as information that comes from an external source (e.g., from a coach or a therapist), and can complement intrinsic feedback when sensory information cannot be reliably used for performance evaluation. For example, a dancer that holds a specific posture, receives input from sensory receptors (e.g., muscle spindles, joint receptors, skin receptors), but based on this information it can be difficult to evaluate the performance without augmented feedback, especially for beginners. For a better understanding of how augmented feedback affects motor learning, current research aims to scrutinize the underlying cognitive mechanisms based on specific neural correlates. Hence, the aim of this secondary analysis of previous data (Margraf et al., 2022a; 2022b) is to supplement the neural data with a time-frequency analysis to strengthen the interpretation of the existing data based on event-related potentials (ERPs), and therefore, to examine the mechanisms of neural feedback processing in motor skill learning in more depth.

Regarding augmented feedback, there are different characteristics (e.g., timing: Swinnen et al., 1990; frequency: Marschall et al., 2007; valence: Zobe et al., 2019) that play essential roles in motor skill learning. Especially the feedback valence (positive or negative) has strong influence on the learning progress and motor automatization (Agethen & Krause, 2016; Wulf et al., 2010; Zobe et al., 2019). Providing feedback as outcome information of negative valence is assumed to increase attentional involvement in the planning and execution of motor tasks. As a result, practice conditions with high frequent negative feedback or unsuccessful outcome are accompanied by a lower degree of automatization, than practice conditions with more frequent outcome information of positive valence (e.g., *Error-Provoked-Attentional-Control-Hypothesis [EPAC-Hypothesis]*: Krause et al., 2018; *Explicit-Hypothesis-Testing-Hypothesis*: Masters & Maxwell, 2004).

Motor learning may be implicit (sometimes also referred to as procedural) or explicit. While implicit learning occurs without awareness and is unintended (Williams, 2020), explicit learning is conscious and involves cognitive effort. With respect to augmented feedback, there are several cognitive mechanisms, which drive (motor) learning (e.g., unsupervised learning, supervised learning, and reinforcement learning [Caligiore et al., 2019]; error-based learning versus reinforcement learning [Luft, 2014]). In the following, the focus will be on supervised and reinforcement learning. Supervised learning is characterized by a comparison of the actual outcome with the desired behavioral goal based on quantitative error-information (Caligiore et al., 2019), and might be rather associated to explicit learning. Reinforcement learning on the other hand, is more related to the processing of rewards / punishment based on qualitative (or categorical) feedback information and is associated to implicit learning (Hinneberg & Hegele, 2022). It can be assumed that these mechanisms do not work individually, but interact with each other (Caligiore et al., 2019). On a neural level, the impact of the valence of augmented feedback in relation to the actor`s own performance evaluation (based on intrinsic feedback information) is described in the *Reward-Prediction-Error-Hypothesis of Dopamine* (Glimcher, 2011; Schultz et al., 1997). An outcome better than expected leads to an increased firing-rate of dopaminergic midbrain neurons and thus, to long-term potentiation and learning. Otherwise, an outcome worse than expected decreases the dopaminergic firing-rate and leads to a disinhibition of the dorsal ACC, and therefore, activates attention-related areas to correct deficient behavior.

The neural correlates of processing valence-dependent feedback in the motor domain (e.g., Joch et al., 2018; Krause et al., 2020; Lohse et al., 2014; Margraf et al., 2022a; Reuter et al., 2020), and long-term learning (i.e., retention, automatization) (Margraf et al., 2022b) have been recently revealed by analysing ERPs of the human electroencephalogram (EEG). Of particular interest were the feedback-related negativity (FRN) and the late fronto-central positivity (LFCP). While the FRN was discussed in association to prediction errors in reinforcement learning (e.g., Glazer et al., 2018; Walsh & Anderson, 2011), the LFCP was associated to more complex feedback processing and supervised learning (e.g., Arbel et al., 2013, Krause et al., 2020). As an ERP only carries the information of an EEG signal that is time- and phase-locked to the stimulus (e.g., feedback onset, FBO), the underlying cognitive processes might be more distinctly represented in the frequency-domain, which can also reflect non-phase locked neural activity (e.g., Cohen, 2014; Luck, 2014). Hence, the respective frequency-band data should strengthen and supplement the interpretation of the existing ERP data. In the following, time-frequency data related to a specific frequency range (frequency-band) is referred to as 'activity', the amount of energy of the specific frequency-band at a point of time is referred to as 'power' (Cohen, 2014). There is a growing body of research examining time-frequency data related to the processing of action outcomes (e.g., augmented feedback, rewards, and punishment), both, in terms of outcome anticipation and in terms of feedback processing (for a review: Glazer et al., 2018). In the following, the focus will be on frontal theta-band activity (4-7 Hz), which is associated to feedback processing, and further discussed in relation to the FRN (for a review: Glazer et al., 2018).

Frontal Theta-band Activity (4-8 Hz)

In humans, band-specific theta activity can be found in different areas of the brain and is associated with cognitive processes on a higher level, such as memory encoding and retrieval or working memory retention (Amin et al., 2012; Cavanagh & Frank, 2014; Ward, 2003). There are several frontal ERPs (e.g., error-related negativity [ERN]; FRN; N2; correct-related negativity [CRN]) that are elicited by different events, like negative feedback, errors, conflict, and unexpected/surprising outcomes (Cavanagh & Frank, 2014). Although, these events are discussed with respect to the performance monitoring system, they were all found to be differentially sensitive to response or feedback features, e.g., valence, novelty, or stimulus-response conflict (Luft, 2014). In this regard, it is interesting that especially frontal theta is assumed to be sensitive for all those events (negative feedback, errors, conflict, unexpected outcomes) that elicit one of the ERP components mentioned (Cavanagh & Frank, 2014; Luft, 2014). That is, beside all differences, the ERP components all seem to have a share in frontal theta-band activity in their spectral composition (Cavanagh & Frank, 2014). All events (negative feedback, errors, conflict, unexpected outcomes) that elicited the different ERPs (i.e., FRN, ERN, CRN, N2) have in common, that they require behavioral adjustments. Therefore, frontal theta-band activity is discussed as a general indicator signaling the need of top-down control to adjust behavior (Cavanagh & Frank, 2014).

With respect to feedback processing, a range of studies found increased theta-band activity following negative feedback (e.g., probabilistic learning task: Cavanagh et al., 2010; time-estimation task: Van de Vijver et al., 2011; gambling task: Williams et al., 2021, toy-gun shooting task: Lange & Osinsky, 2021; for a review: Glazer et al., 2018, Luft 2014), but there are exceptions (gambling task: Christie & Tata, 2009). As frontal theta-band activity is assumed to be generated in the medial frontal cortex and in parts of the ACC (Christie & Tata, 2009; Luu et al., 2003), which is also considered to be the generator of the FRN (e.g., Hauser et al., 2014), it is reasonable to suspect that these components might somehow be connected. In line with this suspicion, Hajihosseini and Holroyd (2013) found a positive correlation of total theta power and FRN-amplitudes in a time-estimation task. In more detail, they observed that the correlation was larger for the phase-locked (evoked) part of theta-band activity, than for the non-phase-locked (induced) part. Interestingly, the data of Hajihosseini and Holroyd (2013) also revealed that evoked theta-band activity was sensitive to outcome valence, while induced theta-band activity was sensitive to outcome probability. This provides evidence that frontal theta-band activity appears to be involved in different processes.

According to the *Reward-Prediction-Error-Hypothesis of Dopamine*, described above (e.g., Glimcher, 2011; Schultz et al., 1997), negative outcomes should lead to an activation of areas for attentional control to correct errorful behavior. Therefore, increased frontal theta-band activity is linked to subsequent behavioral adaptations after undesirable outcomes. In cognitive tasks, theta-band activity covaried with post-error slowing (i.e., trial-to-trial increase in reaction times; probabilistic learning: e.g., Cavanagh et al., 2010; flanker task: e.g., Valadez & Simons, 2018), which is assumed to be induced by an increase of cognitive processing. Enhanced theta-band activity was also found to be a predictor for success in trial-to-trial behavioral adaptations in the cognitive domain (e.g., time-estimation task: Van de Vijver et al., 2011; visual-discrimination task: Cohen & van Gaal, 2013).

Aim of the present study

In the present study, a secondary analysis is carried out to scrutinize the frequency-band specific neural correlates of feedback-processing during the extensive practice of a novel motor task. Evoked (phase-locked) data will be analyzed to reveal a potential basis of the frontal feedback-locked ERPs that were analyzed before (FRN, LFCP; Margraf et al., 2022a; 2022b) in a certain spectrum in the frequency domain. In specific, the FRN might have a neurophysiological basis in phase-locked theta-band activity. Research related to the LFCP does not yet exist. Induced (non-phase-locked) data will be analyzed to reveal cognitive processes that cannot be revealed by the phase-locked data, but also might be associated to the event (valence-dependent feedback) or might be induced or moderated by the cognitive processes (e.g., reinforcement learning, supervised learning) underlying the ERPs (FRN, LFCP). The frequency data is further scrutinized with regard to its correlation with practice-related changes, short-term behavioral adaptations, and long-term learning (especially automatization) (Margraf et al., 2022a, 2022b). As the amount of cognitive processing has an impact on motor learning and automatization, theta-band activity as a general signal that cognitive control is needed, is likely to influence long-term learning effects. To the best of our knowledge, research in this field with respect to time-frequencies is a desideratum in the motor domain. There are studies in the cognitive domain, which claim to investigate learning, but instead scrutinize short-term behavioral adaptations or short-term acquisition performance within one experimental session (e.g., trial-to-trial changes: Van de Vijver et al., 2011). In contrast, here, learning is referred to as relatively permanent changes of performance capabilities that are measured after at least one night of sleep with respective changes in long-term memory (e.g., Blischke et al., 2008; Schmidt & Lee, 2005). Therefore, participants learned a complex movement sequence with the forearm using a lever device, consisting of elbow-extension-flexion movements with three movement reversals across five practice sessions. EEG was recorded in the first and last practice session. The degree of automatization was tested using a dual-task paradigm, by adding a cognitive n-back task.

Hypotheses

Based on previous results (e.g., Cavanagh et al., 2010; Williams et al., 2021), it is predicted, that frontal theta power (as a signal that cognitive control is needed) is likely to be higher after negative as compared to positive feedback (*H1.valence-dependent processing)*. With respect to an increasing amount of practice, it is expected that frontal theta power is likely to decrease after an extensive practice phase (*H2.practice-related changes).* Similar to what was reported in other studies (e.g., Cohen & van Gaal, 2013; Van de Vijver et al., 2011), it is further expected that increased frontal theta power is likely to predict larger subsequent behavioral changes (error correction) (*H3.behavioral adaptations*), especially after negative feedback. Regarding motor automatization, it is assumed that lower frontal theta power during practice is likely to predict larger dual-task cost reductions after extensive practice (*H4.automatization*), especially in the later practice phase. With respect to frontal ERPs, it is expected that frontal theta power is likely to be correlated to the amplitudes of frontal ERPs with respect to both valence categories (*H5.frontal ERPs*), as it was reported for the FRN (e.g., Hajihosseini & Holroyd, 2013). In absence of reports for the LFCP, the expectations here are based on an explorative analysis.

Methods

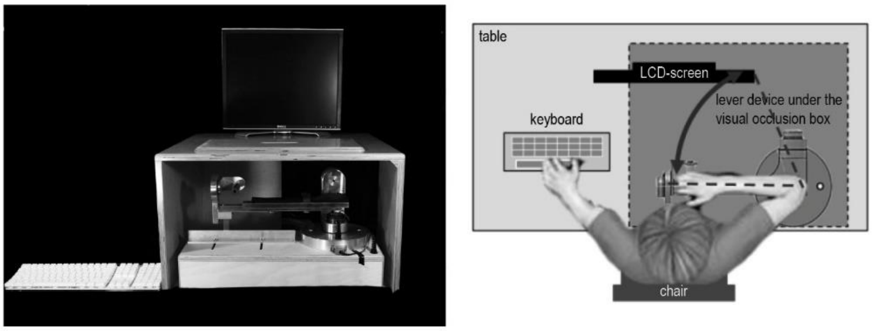
The methods with respect to the experimental setup, the tasks, and the procedures were already described in detail in Margraf et al. (2022a, 2022b). The following descriptions are therefore limited to the relevant aspects for this secondary analysis.

Participants

Thirty-seven (of 38 participants included in the primary analysis, Margraf et al., 2022a, 2022b) undergraduate university students (20 females; mean age = 20.89 ± 1.68; 36 right-handed [German version of the Edinburgh Handedness Inventory, Büsch et al., 2010]; normal or corrected to normal vision, no lesions of the upper limbs) were considered for the final sample. Originally, a total of 43 participants were tested, but due to technical problems during EEG recording, too many artifacts in the EEG data (less than 70% artifact-free trials per condition and session), or cancelation of the experiment, five participants were excluded. One more participant had to be excluded because of a malfunctioning electrode (F3), that was not needed in the primary analysis. Participants gave written consent to take part in the study after being informed about the procedure. Course credits were granted for participation, and money was awarded to the best three performances. The study was approved by the ethics committee of the German Psychological Society (DGPs).

Figure 1

Apparatus and Experimental Setup



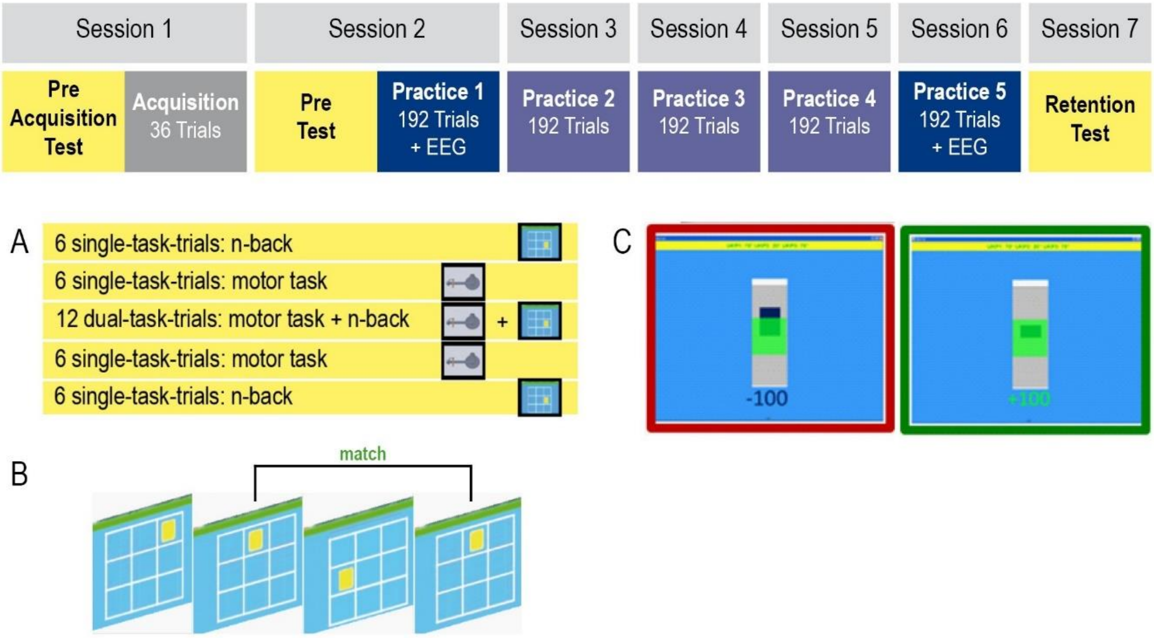
*Note***:** On the left side: The apparatus with the arm-lever device placed under the wooden box, the monitor and the keyboard. On the right side: The experimental setup is shown with the participant sitting in front of the setup. The right arm is placed on the lever in 0°-position, the left arm is placed on the keyboard (Reprinted from Margraf et al., 2022a, Copyright [2021], with permission from Elsevier).

Apparatus and task

Participants practiced a right elbow-extension-flexion sequence in a pretest-posttest-design, executed with an adjustable underarm lever device. The task was to execute a sequence of elbow-extension and elbow-flexion movements with three reversals at 70°, 20°, and 70°, measured in relation to the start-position of the lever device, and to keep the movement time of the 3-movement sequence below 1800 ms. The sequence was finished by crossing the start-position. The experimental setup is shown in Figure 1 (for detailed technical information see Margraf et al., 2022a).

Figure 2

Overview of the Experimental Sessions



Note: In the top row the different experimental sessions (1 – 7) and their content are listed. Session 1 was for formalities and acquistion, followed by an extensive practice phase from Session 2 up to Session 6. EEG was recorded in Practice 1 and Practice 5. The degree of motor automatization was tested under dual-task-conditions in Session 1 (pre-acquisition test), in Session 2 (pre-test), and in Session 7 (retention test). The structure of the test can be found in (**A**). (**B**): Example of a cognitive n-back task trial. (**C**): Feedback during the practice phase, with the blue bar presenting the direction and the magnitude of the error for the reversal with the largest deviation from the goal value. The green transparent bar serves information whether the performance was within the bandwidth based on the median of the last 12 trials, or not. An example for negative feedback was displayed on the left side (red outline): The actual performance was outside of the bandwidth, the participant lost 100 points. An example for positive feedback was displayed on the right side (green outline): The actual performance was within the bandwidth, the participant earned 100 points. (modified according to Margraf et al., 2022a, Copyright [2021], with permission from Elsevier).

Procedures

The study comprised a total of seven experimental sessions that had to be completed within 14 days with at least 24 hours between successive sessions. The criterion task was practiced in five extensive practice sessions (192 trials each). The learning progress (degree of automatization) was measured three times (T0: pre-acquisition test in Session 1; T1: pre-test in Session 2; T2: retention test in Session 7) using a dual-task paradigm. An overview of the experimental sessions can be found in Figure 2. Task-instructions were provided via presentation slides on the monitor and standardized verbal comments of the experimenter during all experimental sessions.

During the practice phase (Session 2 up to Session 6) feedback was given after every trial as a bar graph indicating the direction and the magnitude of the error, but only for the reversal with the largest deviation from the goal-value, without information on the reversal's identity (i.e., first, second, or third reversal point). For more information about the rational for creating a rather high feedback ambiguity see Margraf et al. (2022a). Further, the feedback was based on a performance adaptive bandwidth for positive feedback (defined by the median of the last block of twelve trials), displayed as a green transparent bar that overlaid the blue error bar (see Figure 2, C). Participants earned 100 points, if they performed within the given bandwidth (positive feedback) and lost 100 points if their performance was outside of this bandwidth (negative feedback). This manipulation results in approximately equal amounts of positive and negative feedback. Feedback was presented after the time window for movement execution was closed. The 192 trials of a practice session were divided into 4 blocks of 48 trials each, with a self-determined break between the blocks.

A visual-spatial n-back (2-back) task served as an additional task to test the amount of automatization of the criterion motor task by means of a dual-task paradigm (the structure of the test can be found in Figure 2, A). Yellow rectangles (9 per trial) were presented in a 3 x 3 matrix in randomized order (Figure 2, B). Participants were asked to respond to matches between the current rectangle position and the second-last one with a key press. Omitted matches without a key press, and key presses without a match were counted as errors. The trials of the motor-task began by putting the arm into the starting-position. After a red bar at the upper edge of the screen switched to green, participants were allowed to execute the motor task within the given time window for movement execution. The execution had to be finished before the bar turned to red again after 3000 ms. An acoustic signal marked the change of colors of the bar. During the time window for movement execution (3000 ms), participants had to execute the 3-movement sequence within a maximum movement time of 1800 ms. A dual-task trial started with the n-back task. When the red bar at the upper edge of the screen turned to green, the participants were allowed to perform the motor task. While the motor task had to be executed, the n-back task continued, so that both tasks had to be performed concurrently. During dual-task trials, participants were instructed to prioritize the motor task. No augmented feedback was given in the dual-task trials, neither for the motor task, nor for the n-back-task. A more detailed description of the procedures can be found in Margraf et al. (2022a, 2022b).

EEG recordings

EEG was recorded with a 16-channel AC/DC amplifier (V-amp, Brain Products, Munich, Germany). Active scalp electrodes (based on Ag/AgCl sensors) were applied with an electrode cap (actiCAP, Brain Products), according to the 10-20 system. Active electrodes were placed on F3, FCz, Fz, F4, C3, Cz, C4, P3, Pz, and P4. The ground electrode was set on FPz, online reference was set on FC6, and one more electrode was placed on each mastoid. To measure horizontal and vertical eye movements additional eye electrodes were placed laterally of both eyes, as well as above and below the right eye. Impedances were kept below 20Ω. EEG data were recorded with a sampling rate of 500 Hz with special software (BrainVision Recorder 2.0, Brain Products, Munich, Germany). To synchronize the EEG with the feedback onset, a photodiode (BPW21R, Vishay) was attached to a 1.5 cm^2 area in the right lower corner of the feedback screen. The corresponding area was shielded with black adhesive tape and changed in brightness from dark to light with feedback onset. The data of the photodiode was sampled with the AUX-channel of the amplifier.

Data analysis

With respect to the behavioral data, all trials that contained less or more than three reversals were excluded. Trials in which the movement time of 1800 ms was exceeded, were kept, if they were executed within the execution interval of 3000 ms. Related to practice effects, analysis focused on the first and last practice (Session 2 and Session 6). The absolute error (AE) was used as a measure of movement accuracy and the variable error (VE) was examined as a measure of movement consistency. For the AE, the differences between the actual value and the goal value were calculated for each reversal in angular degrees. The mean of the three differences in one trial was used as the AE in this trial. The mean AE was then calculated for 8 blocks of 24 successive trials for each of the two practice sessions (Practice 1, Practice 5). The VE was defined as the mean of the standard deviations for each of the three reversals in the 24 trials of one block. Afterwards, the mean VE was calculated for the 8 blocks of the two practice sessions (Practice 1, Practice 5). The data can be found in Table 1 in the supplements (for a detailed description of the analysis see Margraf et al., 2022a). To evaluate the degree of motor automatization, the dual-task-tests of Sessions 1, 2, and 7 were analyzed. For the cognitive n-back task, the mean error per trial was calculated. For the movement task, the absolute (accuracy) and the variable (consistency) error were calculated for each trial. Dual-task costs were evaluated with respect to the cognitive task and were calculated as the difference between n-back errors that were made in the single-task and the dual-task condition. The data can be found in Table 2 in the supplements (for a detailed description of the analysis see Margraf et al., 2022b).

Analyses of the neural data were done with Brain Vision Analyzer 2.0 (Brain Products, Munich, Germany). Raw EEG data were offline filtered with a 0.1 Hz high-pass filter (zero phase shift Butterworth filter) and re-referenced to averaged mastoids. Ocular artifacts were corrected by using the semiautomatic mode of the ocular correction algorithm of the analyzer based on Independent Component Analysis (ICA). Triggers set by the photodiode were exported and imported again after feedback valence was defined. EEG data were segmented time-locked to feedback onset. Epochs started 800 ms before feedback onset and ended 2000 ms after feedback onset. Epochs were baseline corrected in the time-domain to avoid artifacts in the frequency domain (Herrmann et al., 2014) with a time window ranging from -560 ms to 0 ms relative to the feedback trigger. The semiautomatic mode of the artifact rejection algorithm of the Brain Vision Analyzer was used to remove segments containing amplitudes exceeding ±75 µV, as well as segments containing fluctuations of amplitudes exceeding 100 µV from peak to peak. The remaining segments were visually inspected twice by two independent raters. Segments evaluated as containing artifacts by both raters were removed.

For time-frequency decomposition, the complex Morlet wavelet transform of the Brain Vision Analyzer was used, as it is the most common method in the neuroscience literature (Cohen, 2014; Williams et al., 2021). The data were analyzed by Gaussian sine waves, a Morlet parameter of 6, in the frequency range from 1 – 30 Hz in 40 logarithmic steps. A baseline normalization (based on a subtraction method) from -500 ms to -200 ms before FBO was applied to the data.

The total frequency power spectrum was conducted by averaging all segments in terms of valence (positive, negative) and of time (Practice 1, Practice 5) for each participant after the Morlet wavelet transform was performed. The phase-locked frequency power spectrum (evoked power) was conducted by averaging the segments (as explained above), before the Morlet wavelet transform was performed. The non-phase-locked frequency power spectrum (induced power) was then detected in accordance with Tallon-Baudry and Betrand (1999) by subtracting the evoked power from the total power. Theta-band activity was defined as a frequency range from 4 – 8 Hz. Grand averages for each condition were calculated. The time window for the frequency-specific activity was chosen based on peak activity visible on the averaged plots and was defined from 200 up to 450 ms after FBO. Mean power within this time-window was exported for each participant. The current analysis of frontal theta power focused on the FCz electrode, as it is the most common electrode for this analysis (e.g., Williams et al., 2021). However, the results for the average of the other frontal electrodes (F3, Fz, and F4) can be found in the supplements.

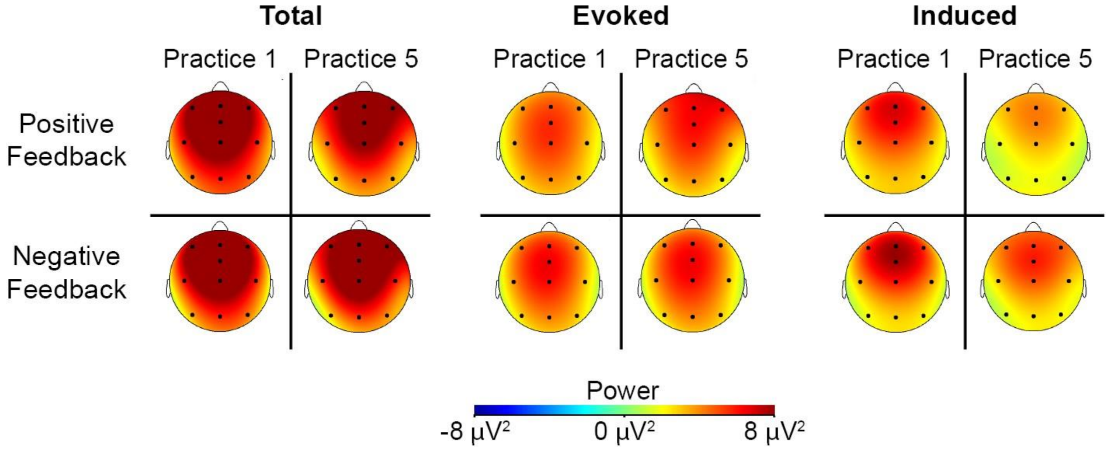
The analysis of coherences of behavioral data and time-frequency-components was conducted as followed: The evaluation of trial-to-trial changes was based on two different types of behavioral adaptations. The change of the maximum absolute error (maxAE change) reflects a goal-directed change of behavior, while the change of the movement over all three reversals (mean reversal change) reflects a goal-independent change of behavior (for more information, see Margraf et al., 2022b). The goal-directed change was evaluated in terms of a decrease or increase of the deviation from the goal value with respect to the maximum error in the following trial. The trials were then labeled as correct (decrease of the deviation) or incorrect (increase of the deviation). This was done for each participant, and for both practice sessions (Practice 1, Practice 5). The goal-independent change was defined as the mean change of the three reversals to the next trial, independent of the deviation from the goal values. The height of the mean change was then labeled as small or large based on the individual median. This was done for each participant, and for both practice sessions (Practice 1, Practice 5). The labeled trials (with respect to the maxAE change and with respect to the mean reversal change) were then set as new triggers for the EEG-data.

Statistical analysis was done with SPSS, 28 (IBM Statistical Package for the Social Science). The alpha level was set to .05 for all analyses. Additionally, partial eta squared was calculated as effect size. P-values that are based on multiple comparisons were Bonferroni-Holm corrected. All results are given as mean values and standard deviations. For the time-frequency-analysis, an ANOVA with repeated measure on *practice* (Practice 1, Practice 5) and *feedback valence* (positive, negative) was calculated separately for evoked (phase-locked) and induced (non-phase-locked) theta-band activity. For the analysis of short-term behavioral changes, the ANOVA was supplemented by the factor *correctness* (correct, incorrect) for the maxAE change, and by the factor *change magnitude* (small, large) for the mean reversal change. Follow-up analyses were conducted with paired *t*-tests and Chohen's *d* as the effect size.

With respect to movement automatization in relation to theta-band activity, correlations between the reduction of dual-task costs and the neural activation were calculated with two-tailed *p*-values separately for evoked and induced theta-band activity. Further, the link between frontal theta-band activity and frontal ERPs was evaluated by calculating correlations with two-tailed *p*-values between theta-band activity (separately for evoked and induced theta-band activity) and the frontal ERPs (separately for the FRN and LFCP).

Figure 3

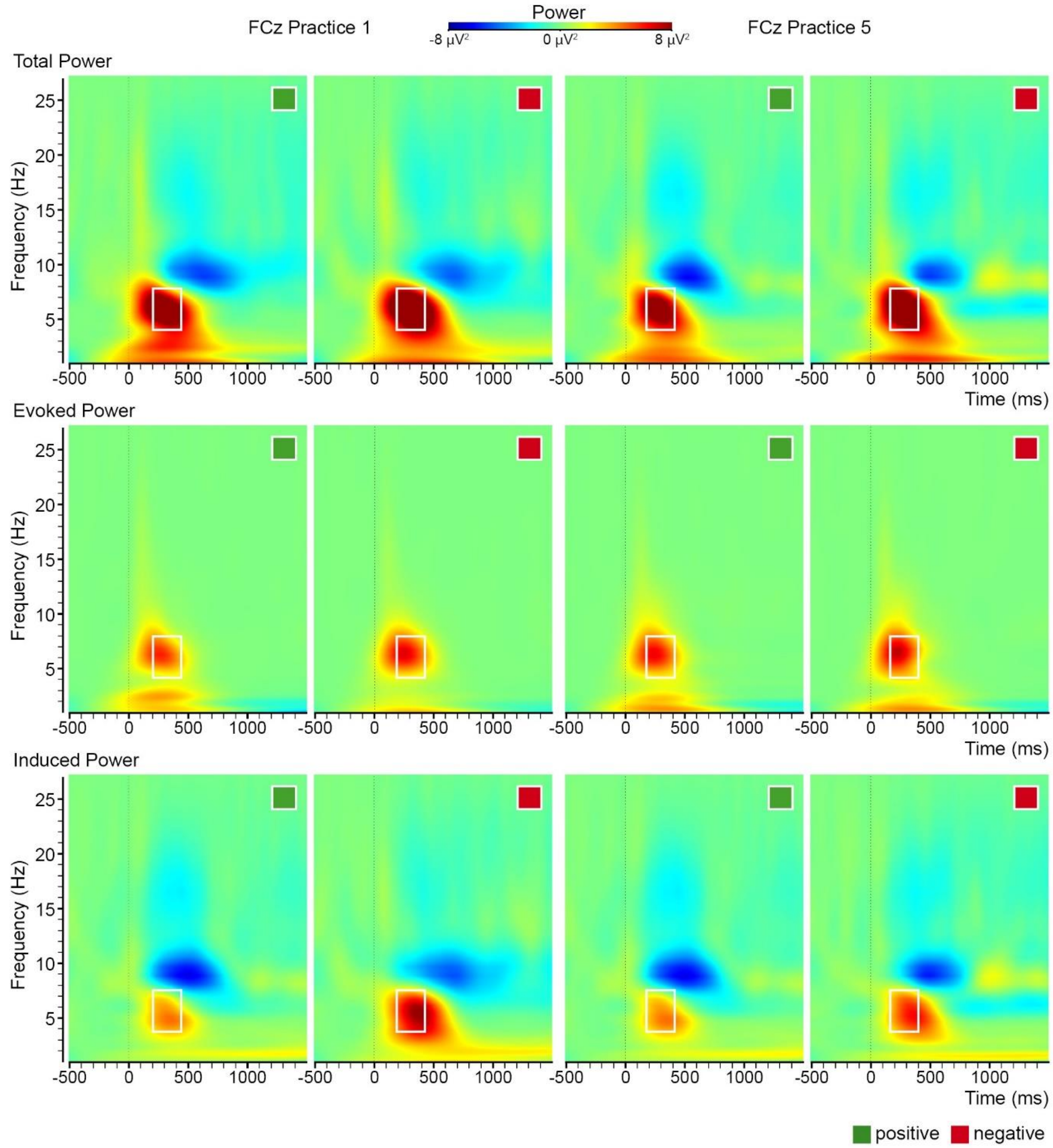
Topography of Theta Activity



Note. Topography of frontal theta activity from 200 up to 450 ms after feedback onset for total power (left), evoked (phase-locked) power (middle), and induced (non-phase-locked) power (right) for positive (upper row) and negative feedback (bottom row) in Practice 1 (left column) and Practice 5 (right column), respectively.

Figure 4

Time-Frequency Plots of the FCz Electrode



Note: Time-Frequency plots at the FCz electrode displaying the frequency range from 1 Hz to 25 Hz within a time window from -500 to 1500 ms around feedback onset (0 ms) given in real power values (µV^2). Feedback conditions (positive, negative) are marked by colored rectangles (green, red) on the upper right edge of each plot. Plots for the early practice phase (Practice 1) are placed on the left, plots for the later practice phase (Practice 5) are placed on the right. The total frequency power spectrum can be found in the top row, the phase-locked frequency spectrum (evoked power) can be found in the middle row, and the non-phase-locked frequency spectrum (induced power) can be found in the lower row.

Results

Valence- and Practice-dependent Results

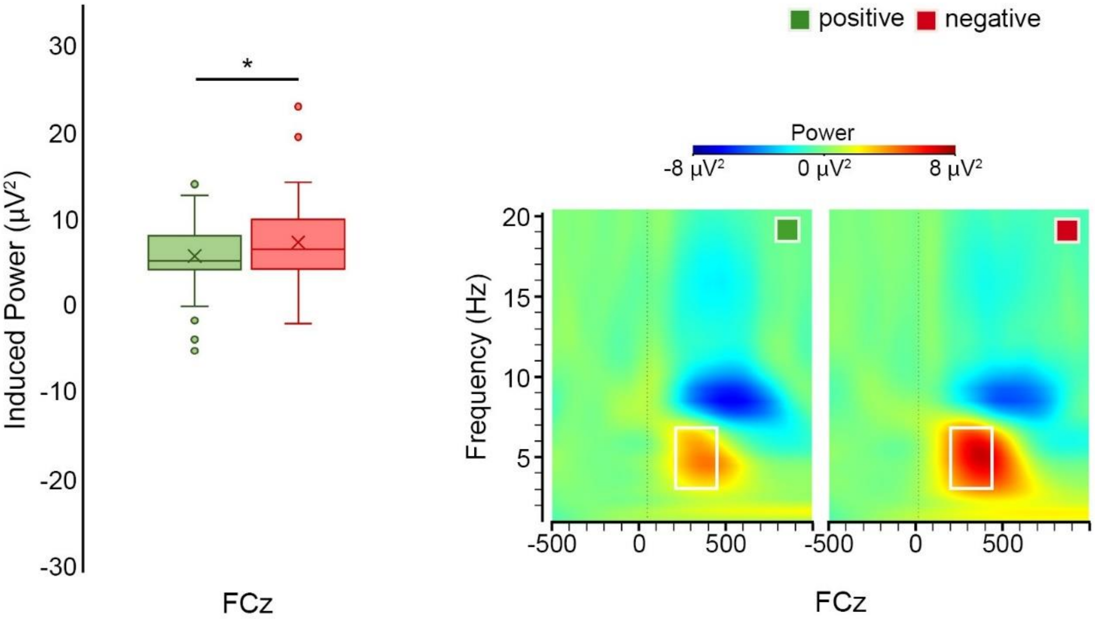
The time-frequency analysis revealed a response about 200 up to 450 ms after feedback onset within the theta-frequency range (4-8 Hz) at the frontal electrodes (see Figure 3 and Figure 4).

Evoked Theta

An overview of evoked theta power at the FCz electrode from 200 to 450 ms after feedback onset can be found in the middle row of Figure 4. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA did not reveal main effects of *valence*, $F(1,36) = 0.45$; $p = .508$; $\eta^2_p = .01$, or *practice*, $F(1,36) = 0.08$; $p = .782$; $\eta^2_p < .01$, and the interaction of *valence* and *practice* was not significant, $F(1,36) = 0.19$; $p = .663$; $\eta^2_p = .01$. Hence, the hypotheses *H1.valence-dependent processing* and *H2.practice-related changes* cannot be supported for evoked frontal theta at the FCz electrode.

Figure 5

Induced Frontal Theta Valence Effect



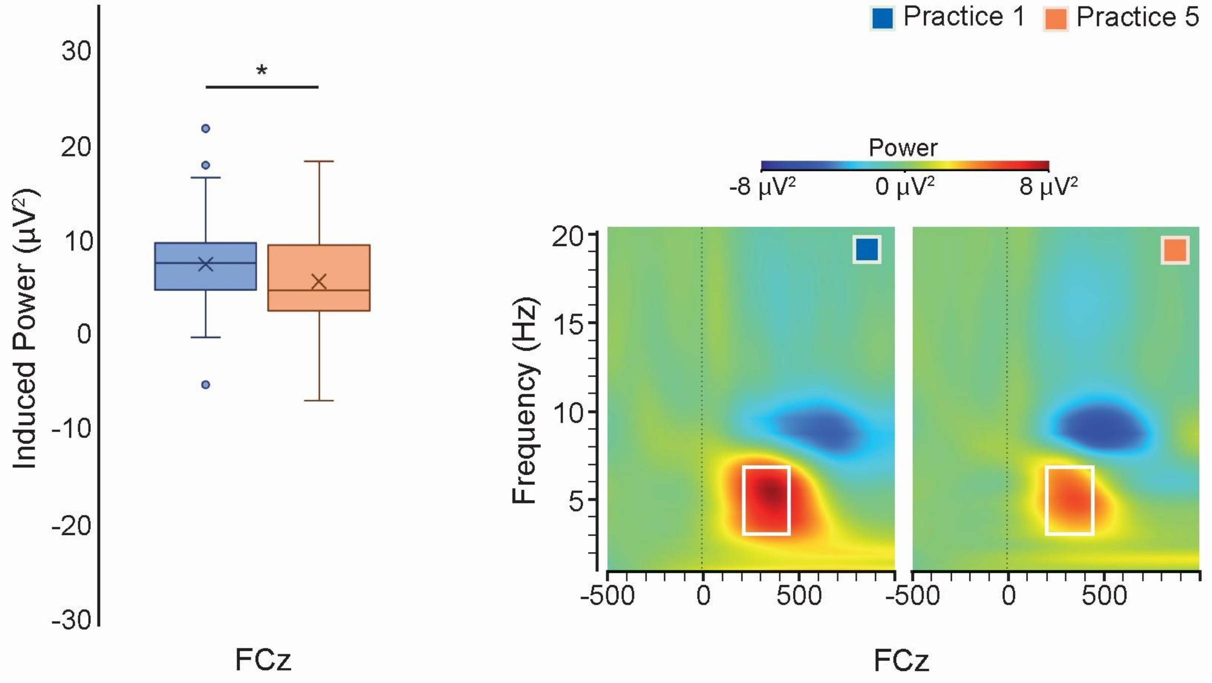
Note: On the left: Induced (non-phase-locked) theta power in microvolts squared for positive (green) and negative (red) feedback independent of practice. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001. On the right: Power spectra of induced (non-phase-locked) theta power for positive (green) and negative (red) feedback. The time range of interest in which significant valence-depenedent differences occurred is outlined with a white square.

Induced Theta

An overview of induced theta power at the FCz electrode from 200 to 450 ms after feedback onset can be found in the bottom row of Figure 4. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA revealed a main effect of *valence*, $F(1,36) = 6.91$; $p = .013$; $\eta^2_p = .16$, and a main effect of *practice*, $F(1,36) = 4.28$; $p = .046$; $\eta^2_p = .11$. Induced theta power was higher after negative feedback ($M = 5.27$; $SD = \pm 4.58$) as compared to positive feedback ($M = 3.83$; $SD = \pm 3.73$). The results are displayed in Figure 5. Induced theta power decreased from Practice 1 ($M = 5.37$; $SD = \pm 4.47$) to Practice 5 ($M = 3.73$; $SD = \pm 4.57$). The results are displayed in Figure 6. The interaction of *valence* and *practice* was not significant, $F(1,36) = 0.28$; $p = .601$; $\eta^2_p = .01$. Accordingly, the hypotheses *H1.valence-dependent processing* and *H2.practice-related changes* can be supported for induced frontal theta at the FCz electrode.

Figure 6

Induced Frontal Theta Valence Effect



Note: On the left: Induced (non-phase-locked) theta power in microvolts squared for Practice 1 (blue) and Practice 5 (orange) independent of feedback valence. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, *p < 0.05, **p < 0.01, ***p < 0.001. On the right: Power spectra of induced (non-phase-locked) theta power for Practice 1 (blue) and Practice 5 (orange) feedback. The time range of interest in which significant practice-induced changes occurred is outlined with a white square.

Summary of Valence- and Practice-dependent Results

The analyses revealed no valence-dependent differences with respect to evoked frontal theta-band activity, while induced frontal theta-band activity was valence-dependent, showing higher theta power after negative feedback. Further, there was no practice-related change with respect to evoked frontal theta-band activity, while there was a practice-induced decrease of frontal theta power with respect to induced frontal theta-band activity.

Short-term Behavioral Adaptations

In the following section, the reported results are reduced to effects with respect to the factor *correctness* (correct, incorrect) for goal-directed adaptations (maxAE change) and with respect to the factor *change magnitude* (large, small) for goal-independent adaptations (mean reversal change).

Evoked Theta

MaxAE Change. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA for evoked theta power did not reveal a main effect of *correctness*, *F*(1,36) = 0.38; *p* = .540; η^2_p = .01 , and no significant interaction was revealed. The hypothesis *H3.behavioral adaptations* cannot be supported for evoked frontal theta power preceding goal-independent behavioral adaptations.

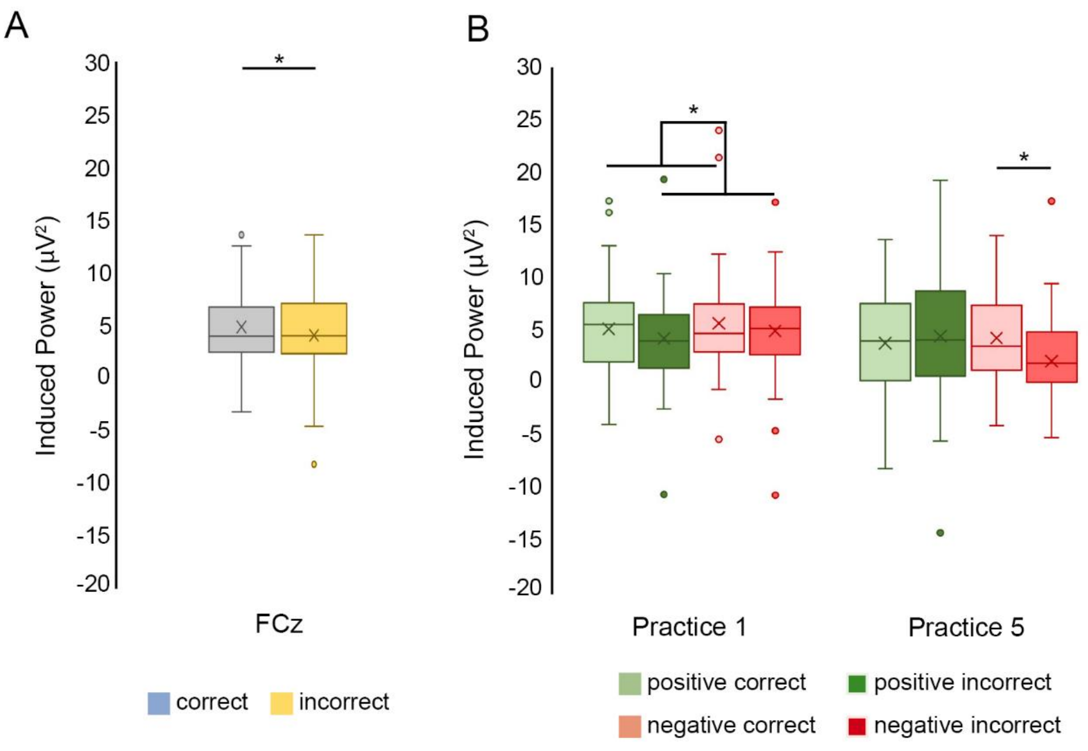
Reversal Change. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*change magnitude*: small, large) ANOVA for evoked theta power did not reveal a main effect of *change magnitude*, *F*(1,36) = 0.67; *p* = .419; η^2_p = .02, and no significant interaction was revealed. The hypothesis *H3.behavioral adaptations* cannot be supported for evoked frontal theta power preceding goal-independent behavioral adaptations.

Induced Theta

MaxAE Change. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA for induced theta power did reveal a main effect of *correctness*, *F*(1,36) = 4.22; *p* = .047; η^2_p = .11. Induced theta power was higher preceding correct changes (*M* = 4.93; *SD* = ±3.90) as compared to incorrect changes (*M* = 4.14; *SD* = ±4.06) of the maxAE (Figure 7, A). Further, there was a significant interaction of *valence*, *practice,* and *correctness*, *F*(1,36) = 4.36; *p* = .044; η^2_p = .11. To disentangle this interaction, a 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA was calculated for each *practice* (Practice 1, Practice 5). For Practice 1, there was a main effect of *correctness*, *F*(1,36) = 5.99; *p* = .019; η^2_p = .14. Induced theta power was higher preceding correct changes (*M* = 5.61; *SD* = ±4.64) as compared to incorrect changes (*M* = 4.79; *SD* = ±4.32) of the maxAE, independent of feedback valence. For Practice 5, there was no main effect of *correctness*, *F*(1,36) = 1.51; *p* = .227; η^2_p = .04, but the interaction of *valence* and *correctness* was significant, $F(1,36) = 5.88$; $p = .020$; $\eta^2_p = .14$. Post-hoc t-tests reveal that induced theta related to negative feedback was significantly higher preceding correct changes ($M = 4.49$; $SD = \pm 4.58$) as compared to incorrect changes ($M = 2.30$; $SD = \pm 6.07$) of the maxAE, $t(1,36) = 2.43$; $p = .020$; $d = .40$, while there was no significant difference preceding correct ($M = 3.99$; $SD = \pm 4.83$) and incorrect ($M = 4.67$; $SD = \pm 6.15$) changes of the maxAE related to positive feedback, $t(1,36) = -0.84$; $p = .409$; $d = -.14$. The results are displayed in Figure 7, B. The hypothesis *H3.behavioral adaptations* can be supported for induced frontal theta power preceding goal-directed behavioral adaptations.

Figure 7

Results for the maxAE Change for Induced Frontal Theta



Note: (**A**) Induced (non-phase-locked) theta power in microvolts squared preceding correct (blue) and incorrect (yellow) corrections of the maximum error (maxAE change) independent from feedback valence and practice session for the FCz eletrode. (**B**) Induced (non-phase-locked) theta power at the FCz eletrode in microvolts squared preceding correct (bright) and incorrect (darker) adaptations of the maximum error (maxAE change) for positive (green) and negative (red) feedback for Practice 1 (left side) and Practice 5 (right side). The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Reversal Change. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*change magnitude*: small, large) ANOVA for induced theta power did not reveal a main effect of *change magnitude*, $F(1,36) = 0.31$; $p = .579$; $\eta^2_p = .01$, and no significant interaction was observed. The hypothesis *H3.behavioral adaptations* cannot be supported for induced frontal theta power preceding goal-independent behavioral adaptations.

Summary of Results on Short-term Behavioral Adaptations

Evoked frontal theta-band activity was not predictive for short-term behavioral adaptations, neither for goal-directed (maxAE change), nor for goal-independent (mean reversal change) changes. With respect to induced frontal theta-band activity, there was also no predictive value for goal-independent changes, but for goal-directed changes. Induced frontal theta-band activity was higher preceding correct changes as compared to incorrect changes of the maxAE. Further, there was a predictive value of induced theta power related to negative feedback in Practice 5 for correct changes of the maxAE.

Long-term Learning (Automatization)

With respect to frontal theta-band activity, it was expected that higher power should predict lower reduction of dual-task costs (i.e., lower motor automatization). However, there was no significant correlation between the reduction of dual-task costs from the pre-test to the retention test and frontal theta power in Practice 1, nor in Practice 5, with respect to both, evoked and induced frontal theta-band activity. The results of the correlation analysis can be found in Table 3 in the supplements. Hence, the hypotheses *H4.automatization* cannot be supported.

Summary of Results on Long-term Learning (Automatization)

The analyses revealed no predictive value of frontal theta-band activity for long-term learning in terms of motor automatization, measured as the reduction of dual-task costs, neither for evoked nor induced theta power.

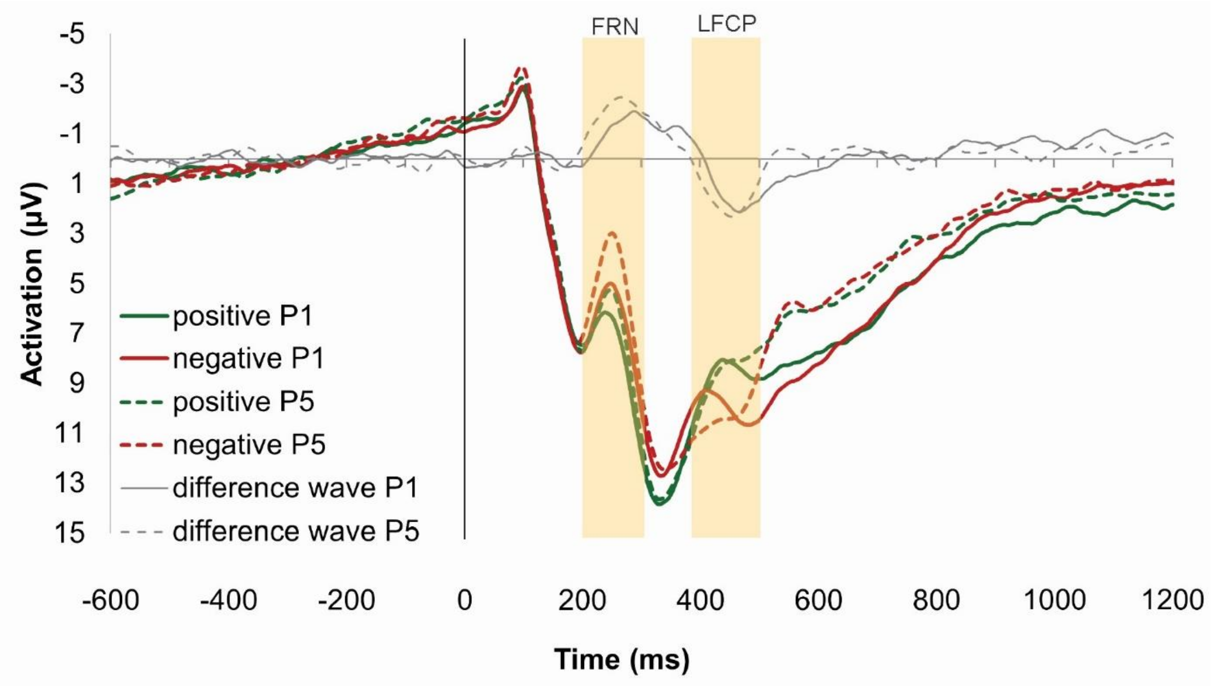
Correlations with Event-related Potentials

In this secondary analysis, it was tested if higher activation within the theta frequency range (evoked and induced) were correlated to frontal ERPs (FRN, LFCP) at the corresponding electrode (FCz). An overview of the amplitudes of the ERPs (FRN, LFCP) can be found in Figure 8. With respect to the FRN, there were no significant correlations between the amplitudes of the FRN and evoked or induced frontal theta power at the FCz electrode. The results of the correlation analysis can be found in Table 4 and are displayed in Figure 4 in the supplements.

Related to the LFCP and evoked theta power there were positive correlations in Practice 5, both, with respect to positive feedback ($r[37] = 0.50$; $p = .008$) and with respect to negative feedback ($r[37] = 0.46$; $p = .020$). Further, regarding induced frontal theta power and LFCP-amplitudes in Practice 1, there was a positive correlation with respect to positive feedback ($r[37] = 0.42$; $p = .010$) and a positive correlation with respect to negative feedback (*r*[37] = 0.58; *p* = .004). Furthermore, there was a positive correlation of LFCP-amplitudes and induced frontal theta power after negative feedback in Practice 5 (*r*[37] = 0.50; *p* = .008). The results are displayed in Figure 9. The hypothesis *H5.frontal ERPs* cannot be supported for the FRN, but for the LFCP. All results of the correlation analysis can be found in Table 4 in the supplements.

Figure 8

ERPs at the FCz Electrode



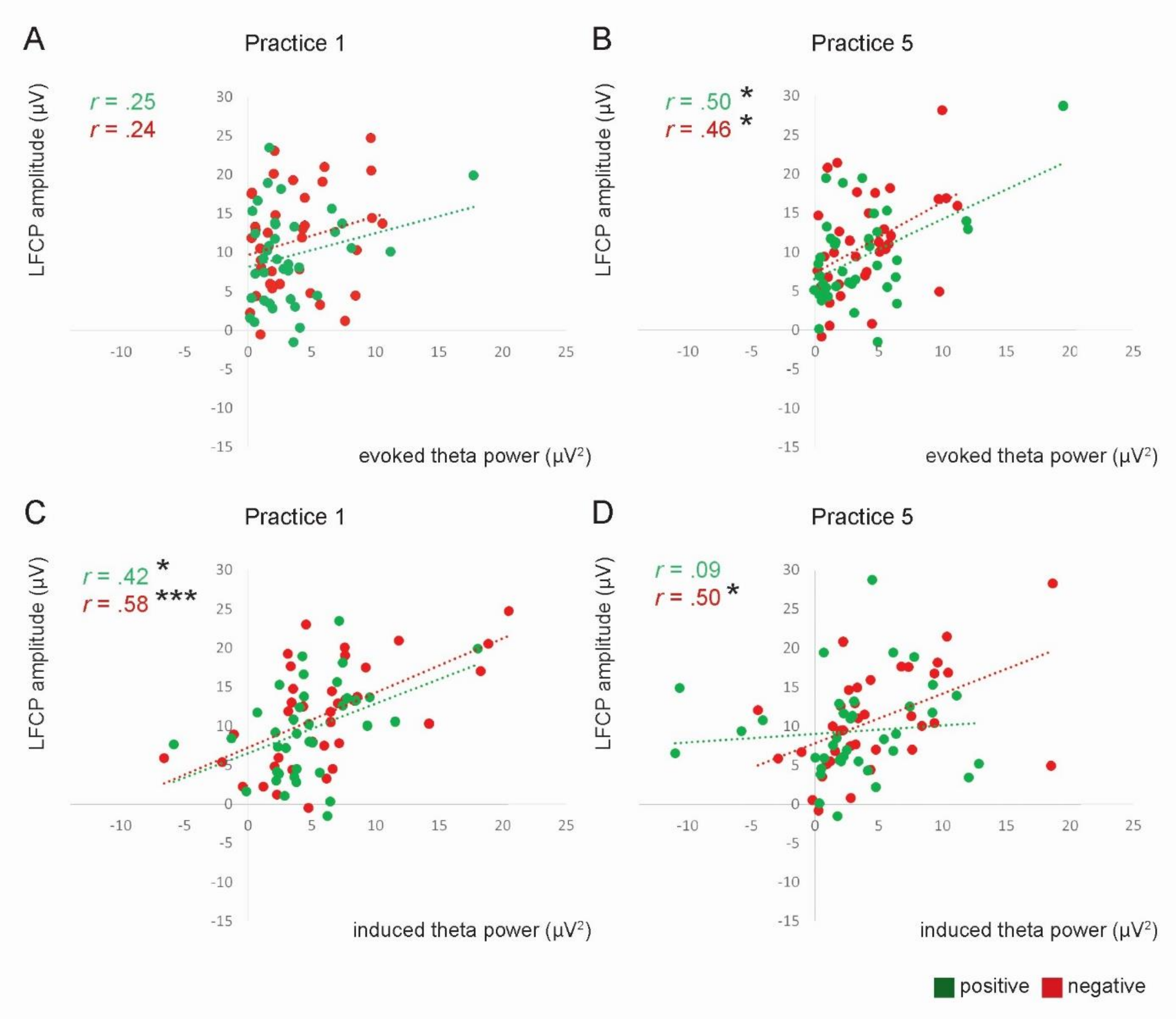
Note. Amplitudes of the ERPs in microvolt (µV) at the FCz electrode for positive (green) and negative (red) feedback in Practice 1 (solid lines) and Practice 5 (dashed lines) and the corresponding difference waves (grey). The FRN peaked about 230 up to 350 ms, the LFCP peaked about 450 up to 550 ms after feedback onset (0 ms).

Summary of Results on Correlations with Event-related Potentials

Frontal theta power at the FCz electrode was not correlated to FRN-amplitudes, neither with respect to evoked, nor with induced theta-band activity. Surprisingly, frontal theta power was positively correlated to LFCP-amplitudes at the corresponding electrode (FCz). This was the case for evoked theta power in Practice 5 and for induced theta power in Practice 1, for both valence conditions, and further for induced theta power in Practice 5, but only for negative feedback.

Figure 9

Correlations of Frontal Theta Activity and Amplitudes of the LFCP at the FCz Electrode



Note: (**A**) Correlations between LFCP-amplitudes and evoked (phase-locked) theta power for positive (green) and negative (red) feedback in Practice 1. (**B**) Correlations between LFCP-amplitudes and evoked (phase-locked) theta power for positive (green) and negative (red) feedback in Practice 5. (**C**) Correlations between LFCP-amplitudes and induced (non-phase-locked) theta power for positive (green) and negative (red) feedback in Practice 1. (**D**) Correlations between LFCP-amplitudes and induced (non-phase-locked) theta power for positive (green) and negative (red) feedback in Practice 5. Significant correlations are marked, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Discussion

This secondary analysis aimed to examine frequency-band specific theta activity related to feedback processing during the extensive practice of a novel motor task to supplement the interpretation of earlier data (Margraf et al., 2022a; 2022b). To this end, participants practiced a sequential arm-movement with 192 trials in each of five practice sessions with successive feedback presentation after every trial. Stage models for motor learning assume a reduction of attentional processing from early to late stages of learning (Fitts & Posner, 1967; Chein & Schneider, 2012). However, motor automatization, as a consequence of extensive motor practice, seems to be moderated by the design of augmented feedback (e.g., Agethen & Krause et al., 2016; Krause et al., 2018). The current study focusses on feedback valence, since according to the EPAC-Hypothesis (Krause et al., 2018), negative feedback events induce an increase in attentional processing.

As expected, the time-frequency analysis uncovered a response to the feedback event that was in the frequency-spectrum within the theta range of 4 to 8 Hz, that spreads across the frontal electrodes and was most pronounced at the FCz electrode (Figure 3). Frontal theta-band activity was separated in a phase-locked part, that is evoked theta, and a non-phase-locked part, that is induced theta. Considering the time-frequency plot (Figure 4), it can be assumed, that evoked theta captured only a small range of the total theta-band activity. A larger part of the total theta response was not phase-locked to the stimulus (feedback onset). These two kinds of theta activity were scrutinized with respect to valence-dependent processing, practice-related changes, short-term behavioral adaptations, and long-term learning in terms of motor automatization. Further, it was tested if frontal theta-band activity can be associated to frontal ERPs related to feedback processing (FRN, LFCP). The results will be interpreted and discussed in detail below.

Evoked Frontal Theta

Related to phase-locked theta-band activity there were no valence-dependent differences in the processing of positive and negative feedback in the current setting. Further, no practice-induced changes could be observed after five sessions of extensive practice. No effects about short-term behavioral adaptations or long-term learning (automatization) could be revealed. Regarding the frontal ERPs, evoked theta was not correlated to the FRN, but to the LFCP in Practice 5.

The phase-locked part of frontal theta-band activity was assumed to reflect the spectral power of the ERP (Cohen, 2014). With respect to the time-frequency plot (Figure 4), the ERP apparently depicts only a small amount of neural feedback processing and is reflected in the upper theta-band range (6-8 Hz). In the current setting, two frontal ERPs were obtained, the FRN and the LFCP (Margraf et al., 2022a). The FRN peaked about 230 – 350 ms after FBO, while the LFPC peaked about 450 – 550 ms after FBO. The phase-locked theta response was pronounced within a time window from 200 to 450 ms after FBO. Based on the latencies, it is not quite clear to which of the ERPs the theta response could be assigned to. The correlation analysis did not reveal an attribution to the FRN (as it was expected), but a weak correlation to the LFCP in the later practice with respect to both valence-categories. Based on these results, it can be assumed that in the current setting, evoked frontal theta-band activity might rather be related to supervised learning than to reinforcement learning, as it was assumed elsewhere (e.g., Cavanagh et al., 2010). Further, the current results suggest that the evoked (phase-locked) part of frontal theta is not just the representation of an ERP in the frequency-domain but reflects an independent process.

However, a consideration of evoked frontal theta-band activity without an attribution to one of the frontal ERPs, does also not match the hypotheses. It is surprising that the valence-effect of evoked frontal theta is absent, because other studies found a difference of evoked theta-band activity related to the feedback valence with higher theta power after negative feedback (e.g., toy-gun shooting task: Lange & Osinsky, 2021; time-estimation task: Hajihosseini & Holroyd, 2013). A first explanation might be found in the feedback design of the current study. While Hajihosseini and Holroyd (2013) used qualitative binary feedback, Lange and Osinsky (2021) did not give augmented feedback, but participants saw whether their shot hit the target or was in the missed-zone and thus, received quantitative feedback about their performance. However, in both studies, there was a clear differentiation in positive and negative feedback categories. In the current study, the transparency of the bandwidth enabled information (magnitude and direction) about the deviation from the goal value to be also obtained in the positive feedback condition. The FRN already appeared to be susceptible to this manipulation, so that the valence effect was rather small, as compared to other studies (Margraf et al., 2022a). While the FRN was mainly discussed in association to feedback processing, frontal theta was interpreted as a more general signal that cognitive control is needed (Cavanagh & Frank, 2014). Therefore, it seems that the error-related information (in the positive feedback display), which can help to improve future performance, is preferably processed as compared to the information that the previous performance was within the actual goal-bandwidth. It seems to be the case that any kind of error information triggers the signal for the attentional control network to be activated for error-correction (EPAC-Hypothesis, Krause et al., 2018), independent from feedback valence.

Further, it might be the case that there are differences in the sensitivity of the neural correlates (evoked frontal theta, frontal ERPs) to certain feedback properties. For example, although Hajihosseini and Holroyd (2013) found a strong correlation of evoked frontal theta and the FRN (or fERN, N200), they argued that the FRN is rather sensitive to reinforcement learning signals, while evoked theta is rather likely to reflect the ACC response to unexpected events. If it can be assumed that evoked frontal theta-band activity is rather sensitive to probability than to valence, the lack of the valence-effect might therefore be explained by equal probabilities of both valence-categories (positive, negative) in the current setting.

Related to the extensive practice phase, it was expected that the demand for cognitive resources would become smaller as the performance increases. This should have been indicated by a decrease of frontal theta power. This was not the case related to evoked frontal theta-band activity. An explanation might be found in the difficulty of interpreting the error information presented in the feedback display. Here it is to note, that participants received only information about the largest error, but no information on the identity of the reversal that was affected. Moreover, the bandwidth for positive feedback was performance adaptive. Thus, also in the later practice phase and with better performance, cognitive resources are needed to identify and to correct the error. The results related to the ERPs already gave indications that the smaller errors in the later practice even led to an increase in activity (FRN, Margraf et al., 2022a), or prevented a decrease (LFCP, Margraf et al., 2022a).

Induced Frontal Theta

There was a large amount of frontal theta-band activity that was not phase-locked to the stimulus (feedback onset) and spreads out over the whole theta range (4-8 Hz), indicating that much of neural feedback processing in motor learning cannot be revealed by the ERPs. The analyses of induced (non-phase-locked) frontal theta-band activity revealed higher theta power after negative feedback as compared to positive feedback. Further, induced theta power decreased after five sessions of extensive practice. Furthermore, there was a predictive value of induced frontal theta power for correct adaptations of the maximum error. With respect to the ERPs, induced frontal theta power was positively correlated to the LFCP.

In the current setting, the valence effect for induced frontal theta-band activity is in line with the *Reward-Prediction-Error-Hypothesis* (Glimcher, 2011; Schultz et al., 1997), stating that outcomes worse than expected trigger a neural signal to activate areas for cognitive control. The current result supports the assumption that frontal theta is a general indicator that cognitive control is needed (Cavanagh & Frank, 2014) to correct behavior (e.g., errors). Moreover, induced frontal theta-band activity did not only indicate that cognitive control is needed, but it was also a predictor for how well this is implemented. In the current setting, induced frontal theta was predictive for goal-directed behavioral adaptations. Induced theta power was higher preceding correct adaptations of the maximum error. In the later practice phase, this was only the case for negative feedback. Other studies (e.g., Cohen & van Gaal, 2013; Van de Vijver et al., 2011) also found enhanced theta power to be predictive for successful trial-to-trial behavioral changes. A higher urgency for cognitive control, indicated by higher theta power, seems to predict a more efficient processing of the error information, and therefore, better error correction. Moreover, as the predictive value of induced theta power was limited to negative feedback in Practice 5, it seems to be the case, that there was a shift of the information that were processed over the course of practice. While in early practice, the focus seems to be primarily on the error information independent from valence (please note here, that error information can also be extracted in positive feedback events in this setting). Whereas in the later practice, the error information is more specifically differentiated according to the valence category, and therefore, primarily the error information from the negative feedback triggers the need for cognitive control.

According to several learning theories (e.g., *Model of Parallel Neural Networks,* Hikosaka et al., 1999) extensive practice should lead to an increased degree of automatic control, indicated by lower activity of attention-dependent areas of the brain. Therefore, it was expected that the neural correlates reflecting attention-related cognitive processes should decrease over the course of practice. In line with this assumption, induced frontal theta-band activity decreased over five sessions of extensive practice, which was also in line with the behavioral data that revealed a decrease of DTC from the pre-test to the retention test (reported in: Margraf et al., 2022b). With an increase in performance and smaller errors in the later practice, the need for cognitive control to correct the error seems to decrease, while attention-independent representations should be established (Hikosaka et al., 1999). Surprisingly, this process from attentional to more non-attentional control does not seem to be reflected in other neural correlates of feedback processing in the current setting. While the FRN even increased after five sessions of practice related to negative feedback, the LFCP did not change in activity at all (Margraf et al., 2022a). This might indicate a dissociation of the involvement of feedback processing (e.g., error detection; reward processing), as reflected in the FRN and LFCP, and the associated involvement of attention, as it might be seen in frontal theta activation. This assumption strongly demands for further investigation in systematic replications.

Another explanation for the decrease of frontal theta power from Practice 1 to Practice 5 might be found in the performance adaptive bandwidth for positive feedback. With an increasing amount of practice and a better performance, the gains became very small in the later practice session. A decrease of frontal theta-band activity after extensive practice could be based in a decreasing willingness to invest cognitive effort, while further improvements do not seem to be achievable, as performance gains are absent or minimal in later practice.

The current results further support the idea, that frontal theta-band activity is rather associated to supervised learning, than to reinforcement learning in the current setting. The analyses revealed no correlation to the FRN (as an indicator of prediction errors in reinforcement learning, e.g., Holroyd & Coles, 2002), but to the LFCP, associated to more complex feedback processing and supervised learning (e.g., Cockburn & Holroyd, 2018, Krause et al., 2020). This was also supported, as both correlates (induced frontal theta, LFCP) were predictive for goal-directed behavioral adaptations (change of the maximum error). It remains to be solved, why other studies found a correlation of frontal theta and the FRN (e.g., Williams et al., 2021) and discussed it, in association to reinforcement learning (e.g., Cavanagh et al., 2010). Based on the feedback design in this study (combining qualitative and quantitative feedback information), the informational basis for both mechanisms (reinforcement learning and supervised learning) is present. However, in the current setting, the quantitative error-information seemed to have a more dominant role in the learning process. Future research is needed to clarify this aspect by systematically varying the feedback characteristics and providing either qualitative or quantitative feedback information.

Predictive Value for Long-term Learning and Automatization

Related to long-term learning with respect to motor automatization (measured as the reduction of dual-task costs from the pre-test to the retention test), no effects with respect to frontal theta-band activity were revealed, neither with evoked, nor with induced theta power. Further, it was expected that higher frontal theta-band activity, as an indicative signal for a higher involvement of attention-dependent processing, should be predictive for a lower amount of reduction of dual-task costs (i.e., motor automatization). This was not the case. Enhanced frontal theta power might only indicate that cognitive control is needed to process the current information but does not predict the amount of attentional processing. Although there are indications, that a higher involvement of cognitive processing early in practice facilitates motor automaticity, as it was found that higher LFCP-amplitudes in early practice facilitates the reduction of dual-task costs (cf., Margraf et al., 2022b), this was not indicated by frontal theta-band activity. At this point, further research is needed to determine if there is an advantage of intensified cognitive processing in early practice for long-term automatization.

Limitations of the Current Study

There are some limitations of the current study design that should be addressed and discussed. The current task and the feedback design cannot be generalized to every motor skill. There are many situations in which the learner can directly see the result of the action (e.g., a ball's flight, a ball that hits or misses a goal). In the current setting, visual movement control was occluded and the feedback was not related to the whole outcome of the task, but instead to a single part that could not be clearly assigned to a specific action. Although the goal of the study was not to model a real-world task, learning situations of this type do exist (e.g., dancers receiving ambiguous feedback for a sequence of postures). However, future research should address this issue to change the task conditions that would better correspond to other tasks (e.g., with visual movement control, an unambiguous assignment of the feedback).

Another point is the high demand for accuracy and consistency of the current task. In real practice scenarios, there might be a performance level, above which further corrections will not be further demanded and a certain margin of error remains. Data of the same basic paradigm with a normative-negative feedback condition revealed that participants are able to reduce the error to a larger extend (compared to the current data), when they are informed that other participants were able to show comparably better performance (Zobe et al., 2019). There seems to be some asymptotic level of performance here. Participants might be less willing to put effort in a further performance improvement. Further research is needed, in which the motivation for further improvements will be held high.

Conclusion

This secondary analysis of the study by Margraf et al. (2022a, 2022b) provided further insights in valence-dependent neural feedback processing during extensive practice of a motor sequence learning task, but also raised several questions. Consistent with the EPAC- Hypothesis (Krause et al., 2018), quantitative augmented feedback provoked activity across frontal components (frontal theta, FRN, LFCP). Similar to the FRN and the LFCP (Margraf et al., 2022a), the induced (non-phase-locked) part of frontal theta-band activity was stronger after negative feedback, which supports the assumption that frontal theta-band activity is a general signal that cognitive control is needed (e.g., Cavanagh & Frank, 2014). According to several stage models for motor learning (e.g., Chein & Schneider, 2012; Fitts & Posner, 1967; Hikosaka et al., 1999), there should be a decrease in attention-related neural processing when attention-independent representations are established. Consistent with these models, the induced part of frontal theta-band activity decreased after five sessions of extensive practice. Surprisingly, this was not the case for the other frontal components (evoked theta-band activity, FRN, LFCP). The present results support the idea of distinct, but overlapping processes in frontal feedback processing (e.g., Peterburs et al., 2016). However, it remains to be solved why some correlates of frontal attentional processing decreased after five sessions of extensive practice, while others did not, even with an increased amount of automatic control, which was confirmed by the behavioral data (Margraf et al., 2022b). However, this secondary analysis demonstrated that not all processes of neural feedback processing in motor practice are reflected by the ERPs. A careful analysis of the ERPs should not be abandoned, but it seems helpful to complement it with a time-frequency-analysis to get further insights.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: LM, DK, and MW all worked on the idea of a secondary analysis of former data, DK designed the study the secondary analysis was based on. Supervision: MW supervised the project. Investigation: DK and LM collected the research data. Data curation: DK and LM were responsible for the handling of the research data. Formal analysis: LM analysed the data, supported by DK. Visualization: LM prepared the figures. Writing – original draft: LM wrote the first draft of the manuscript. Writing – review & editing: LM, DK, and MW commented and revised the manuscript.

Data Availability Statement

Data for this manuscript and supplementary material can be accessed from: https://osf.io/4kqmc/.

Abbreviations

ACC, anterior cingulate cortex; AE, absolute error; CRN, correct-related negativity; DGPs, German Psychological Society; DTC, dual-task costs; EEG, electroencephalogram; EPAC-Hypothesis, Error-Provoked-Attentional-Control-Hypothesis; ERN, error-related negativity; ERPs, event-related potentials; FBO, feedback onset; FRN, feedback-related negativity; Hz, Hertz; ICA, independent component analysis; LFCP, late fronto-central positivity; maxAE, maximum absolute error; ms, milliseconds; PFC, prefrontal cortex; T0, pre-acquisition test; T1, pre-test; T2, retention test; VE, variable error.

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Supplements Chapter III

Behavioral Data

Summary of Relevant Behavioral Results

With respect to the practice sessions, participants significantly reduced the mean absolute error (accuracy) from Practice 1 (*M* = 5.20; *SD* = ±1.64) to Practice 5 (*M* = 3.84; *SD* = ±2.24). This was also true for the variable error (consistency; P1: *M* = 3.04; *SD* = ±0.85; P5: *M* = 2.26; *SD* = ±0.85). For more details of the analysis and the results see Margraf et al., 2022a. With respect to the tests (dual-task tests), participants hit the reversals significantly more accurate and more consistent in the single-task, as compared to the dual-task condition. They were able to reduce the absolute error from the pre-acquisitions test to the pre-test, but not from the pre-test to the retention test. However, they were able to reduce the variable error from the pre-acquisition test to the pre-test, and further, from the pre-test to the retention test. Regarding the amount of automatization, dual-task costs (DTC) were significantly lower in the retention test, as compared to the pre-test. For more details of the analysis and the results see Margraf et al., 2022b.

Table 1

Behavioral Data of the Motor Task (N=38)

	Absolute Error		Variable Error	
	Practice 1	Practice 5	Practice 1	Practice 5
Block 1	5.91 (2.06)	4.33 (1.99)	3.60 (1.32)	2.77 (1.48)
Block 2	5.50 (2.26)	3.92 (2.30)	3.27 (1.24)	2.32 (1.11)
Block 3	5.40 (2.23)	3.75 (2.34)	3.02 (1.14)	2.19 (0.91)
Block 4	5.29 (2.21)	3.90 (2.37)	2.97 (0.95)	2.18 (0.81)
Block 5	4.96 (1.80)	3.69 (2.22)	2.92 (0.90)	2.14 (0.80)
Block 6	5.05 (2.09)	3.77 (2.59)	2.94 (1.00)	2.21 (0.91)
Block 7	4.72 (2.09)	3.73 (2.40)	2.78 (1.00)	2.22 (0.80)
Block 8	4.77 (1.98)	3.66 (2.48)	2.83 (1.04)	2.06 (0.78)

Note. The absolute error relates to accuracy in the criterion motor task and is given in angular degrees and displays the mean of one block of 24 trials. The variable error is related to the consistency in the criterion motor task and is also given in angular degrees and displays the mean of one block of 24 trials (see Margraf et al, 2022a for figures and statistics).

Table 2

Behavioral Data of the Dual-Task Tests and Dual-Task Costs for the N-back error (N=38)

Variable	T0	T1	T2
N-back error			
Single-Task	1.18 (0.60)	0.78 (0.59)	0.61 (0.54)
Dual-Task	2.13 (0.54)	1.65 (0.55)	1.25 (0.59)
Absolute error			
Single-Task	9.54 (4.22)	6.62 (2.80)	5.98 (2.24)
Dual-Task	10.62 (4.76)	7.37 (2.83)	6.28 (2.54)
Variable error			
Single-Task	4.96 (1.75)	3.94 (1.60)	3.38 (1.47)
Dual-Task	5.49 (2.11)	4.26 (1.38)	3.64 (1.62)
Dual-Task Costs			
N-back error	0.96 (0.59)	0.87 (0.60)	0.64 (0.76)

Note. The n-back error is related to the cognitive task and is defined as mean error per trial. The absolute error relates to accuracy in the criterion motor task and is given in angular degrees. The variable error is related to the consistency in the criterion motor task and is also given in angular degrees. During dual-task conditions, participants were asked to prioritize the motor task. Dual-task costs were related to the cognitive n-back task and defined as difference between performance in the single-task and dual-task condition. See Margraf et al., 2022b for figures and statistics. T0: Pre-Acquisition-Test; T1: Pre-Test; T2: Retention-Test.

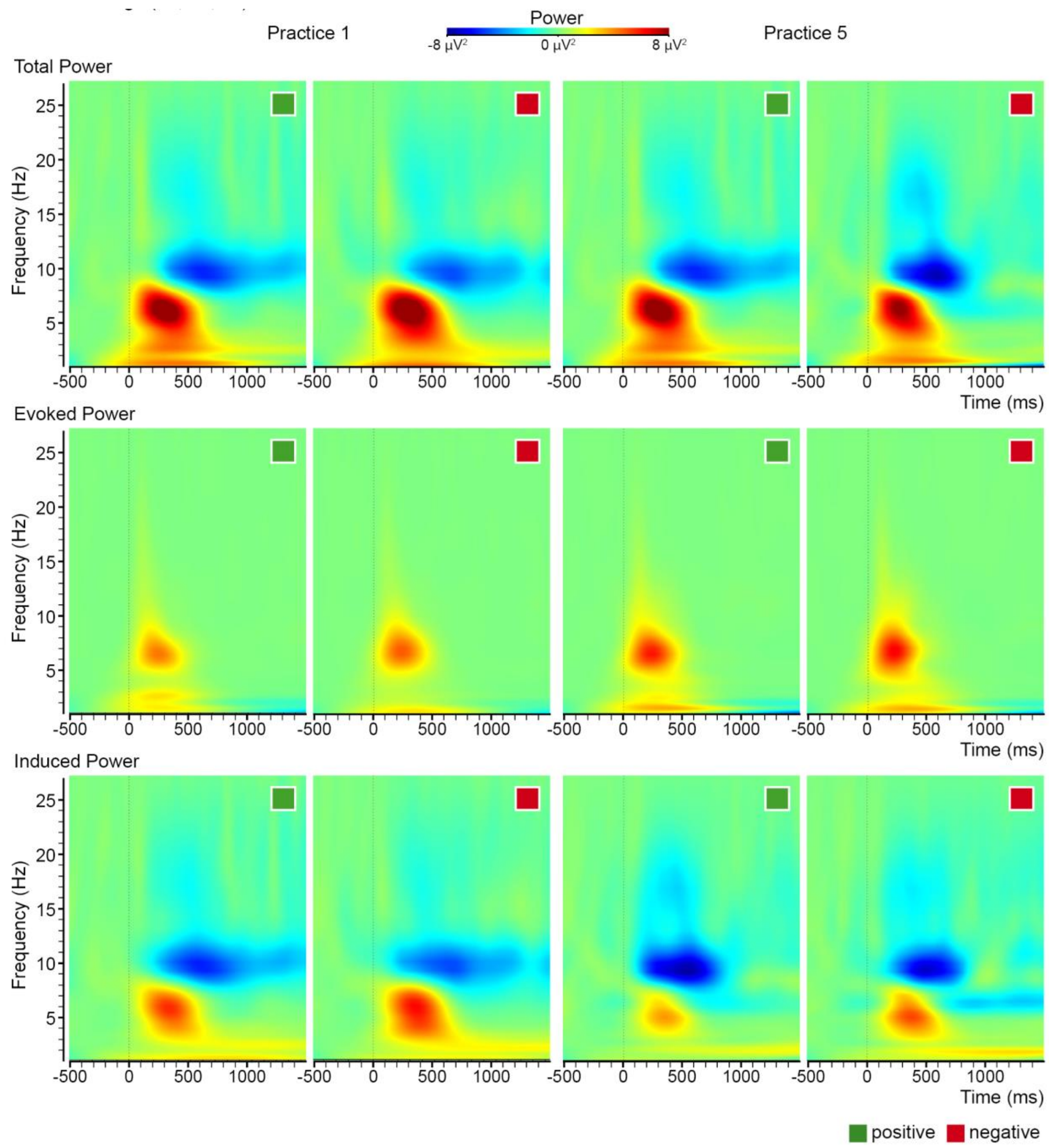
Absolut Maximum Error (maxAE)

In 69.39% of the trials, participants were able to adapt the correct reversal in the next trial. The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA revealed a main effect of *practice*, $F(1,36) = 10.64$; $p = .002$; $\eta^2_p = .23$, and of *valence*, $F(1,36) = 20.05$; $p < .001$; $\eta^2_p = .36$. The mean maxAE decreased from Practice 1 ($M = 7.97$; $SD = \pm 2.20$) to Practice 5 ($M = 6.11$; $SD = \pm 2.96$). Further, the mean maxAE was larger after negative feedback ($M = 7.19$; $SD = \pm 1.92$) as compared to positive feedback ($M = 6.89$; $SD = \pm 1.98$). The interaction of *practice* and *valence* just failed to be significant, $F(1,36) = 3.92$; $p = .055$; $\eta^2_p = .10$.

Additional Analyses of the Neural Data

Figure 1

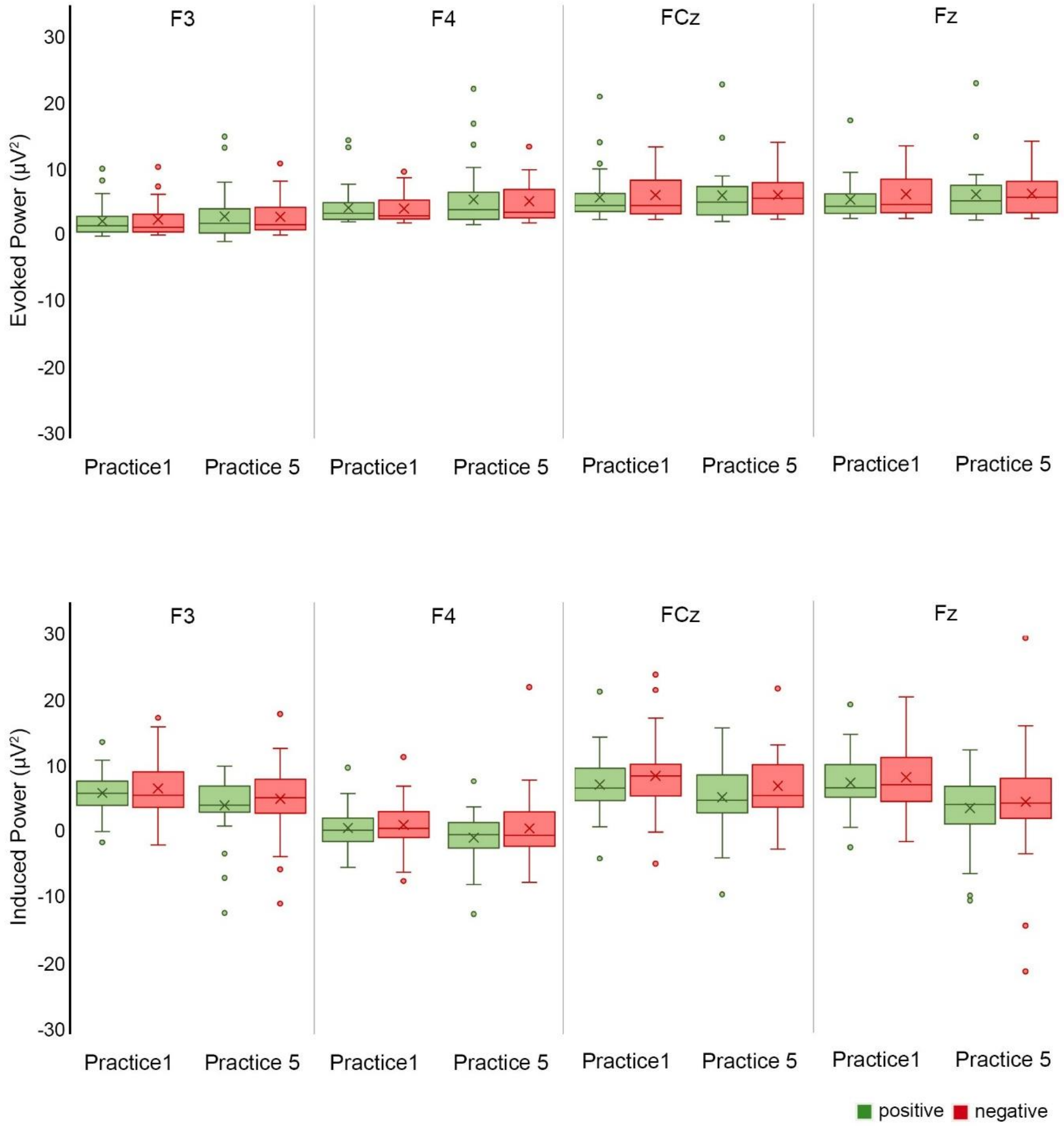
Time-Frequency Plots for Pooled Frontal Electrodes (F3, Fz, F4)



Note. Time-Frequency plots for pooled frontal electrodes F3, Fz and F4, displaying the frequency range from 1 Hz to 25 Hz within a time window from -500 to 1500 ms around feedback onset (0 ms) given in real power values (µV²). Feedback conditions (positive, negative) are marked by colored rectangles (green, red) on the upper left edge of each plot. Plots for the early practice phase (Practice 1) are placed on the left, plots for the later practice phase (Practice 5) are placed on the right. The total frequency power spectrum can be found on in the top row, the phase-locked frequency spectrum (evoked power) can be found in the middle row, and the non-phase-locked frequency spectrum (induced power) can be found in lower row.

Figure 2

Overview Evoked and Induced Frontal Theta Power



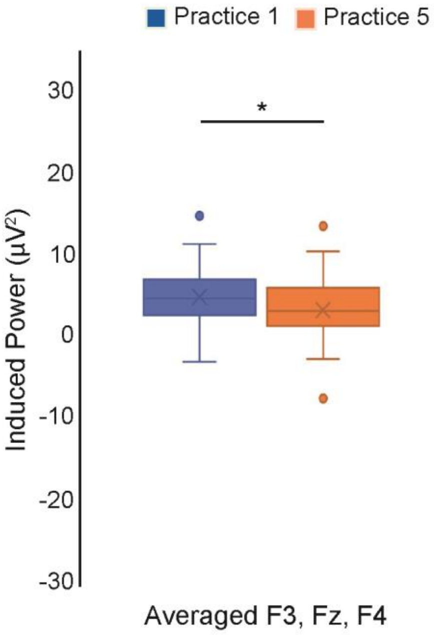
Note: Theta power in microvolts squared for positive (green) and negative (red) feedback for Practice 1 and Practice 5 for the frontal electrodes (F3, Fz, FCz, F4), for evoked (phase-locked) power in the upper row, and inducd (non-phase-locked) power in the bottom row. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box.

Valence- and Practice-dependent Results for the Average across Frontal Electrodes (F3, Fz, and F4)

Evoked theta: The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the average of the frontal electrodes Fz, F3, and F4 electrode did not reveal a main effect of *valence*, $F(1,36) < 0.01$; $p = .997$; $\eta^2_p < .01$, or *practice*, $F(1,36) = 1.96$; $p = .170$; $\eta^2_p = .05$. The interaction of *valence* and *practice* was not significant, $F(1,36) = 0.36$; $p = .555$; $\eta^2_p = .01$.

Figure 3

Induced Frontal Theta Power Practice Effect



Note: Induced (non-phase-locked) theta power in microvolts squared for Practice 1 (blue) and Practice 5 (orange) feedback for the average across the frontal electrodes F3, Fz and F4. The boxes display the median and the 25th and 75th quartiles, whiskers showing the 5th and the 95th percentile. The mean is displayed by a cross and outliers are shown as data points outside of the box. Significant differences are marked, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Induced theta: The 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) ANOVA for the average of the frontal electrodes Fz, F3, and F4 electrode did not reveal a main effect of *valence*, $F(1,36) = 2.72$; $p = .108$; $\eta^2_p = .07$, but of *practice*, $F(1,36) = 6.86$; $p = .013$; $\eta^2_p = .16$. Induced theta power decreased from Practice 1 ($M = 4.36$; $SD = \pm 3.48$) to Practice 5 ($M = 2.74$; $SD = \pm 4.11$). The interaction of *valence* and *practice* was not significant, $F(1,36) = 0.31$; $p = .582$; $\eta^2_p = .01$.

Short-term behavioral Adaptation Effects for the Averaged Frontal electrodes F3, Fz, and F4

Evoked theta. With respect to the AEmax change, the 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA did not reveal a main effect of *correctness*, $F(1,36) = 0.40$; $p = .529$; $\eta^2_p = .01$, and no significant interaction including this factor was revealed. With respect to the mean reversal change, the 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*change magnitude*: small, large) ANOVA did not reveal a main effect of *change magnitude*, $F(1,36) = 0.34$; $p = .563$; $\eta^2_p = .01$, and no significant interaction including this factor was revealed.

Induced theta. With respect to the AEmax change, the 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*correctness*: correct, incorrect) ANOVA did not reveal a main effect of *correctness*, $F(1,36) = 2.96$; $p = .094$; $\eta^2_p = .08$, and no significant interaction including this factor was revealed. With respect to the mean reversal change, the 2 (*practice*: Practice 1, Practice 5) x 2 (*valence*: positive, negative) x 2 (*change magnitude*: small, large) ANOVA did not reveal a main effect of *change magnitude*, $F(1,36) = 0.26$; $p = .615$; $\eta^2_p = .01$, and no significant interaction including this factor was revealed.

Correlation Analysis: Long-term Learning (Automatization)

Table 3

Correlations between Frontal Theta Power and Automatization

	Practice 1			Practice 5		
	r	*p*	p^1	*r*	*p*	p^1
FCz: Evoked theta after positive feedback	<.01	.984	>.999	.14	.408	>.999
FCz: Evoked theta after negative feedback	-.03	.882	>.999	.09	.597	>.999
FCz: Induced theta after positive feedback	.14	.416	.416	.09	.602	.602
FCz: Induced theta after negative feedback	.30	.072	.144	.21	.215	.430
Frontal Average (F3, Fz, F4): Evoked theta after positive feedback	-.03	.841	>.999	.16	.361	>.999
Frontal Average (F3, Fz, F4): Evoked theta after negative feedback	-.07	.671	>.999	.10	.555	>.999
Frontal Average (F3, Fz, F4): Induced theta after positive feedback	.09	.560	>.999	.04	.809	>.999
Frontal Average (F3, Fz, F4): Induced theta after negative feedback	.32	.055	.220	.15	.362	>.999

Note: The degree of automatization was measured as reduction of dual-task-costs in the cognitive n-back task from the pre-test in Session 2 to the retention test in Session 7. Based on multiple comparions the p-values were Bonferroni-Holm corrected.

Summary of Relevant ERP Results (FRN, LFCP)

FRN

The FRN peaked about 250±13ms after FBO in the current setting. The FRN was valence-dependent with more negative amplitudes after negative feedback as compared to positive feedback. Further, amplitudes increased after five sessions of extensive practice, but only with respect to negative feedback. With respect to behavioral adaptations, larger amplitudes of the FRN after negative feedback were predictive for lager goal-independent (mean reversal change) changes, but only in Practice 1. For the detailed description of the results and their interpretation see Margraf et al., 2022a & 2022b.

LFCP

The LFCP peaked about 484±22ms after FBO in the current setting. The LFCP was valence-dependent with more positive amplitudes after negative feedback as compared to positive feedback. There were no practice-related changes of the LFCP after five sessions of extensive practice to be observed. With respect to behavioral adaptations, larger amplitudes of the LFCP after negative feedback were predictive for larger goal-directed (AEmax change) changes, independent from the practice session. Further, there was a positive correlation of LFCP-amplitudes after positive feedback in Practice 1 and the amount of the DTC-reduction (automatization). For the detailed description of the results and their interpretation see Margraf et al., 2022a & 2022b.

Correlation Analysis: Frontal ERPs

Table 4

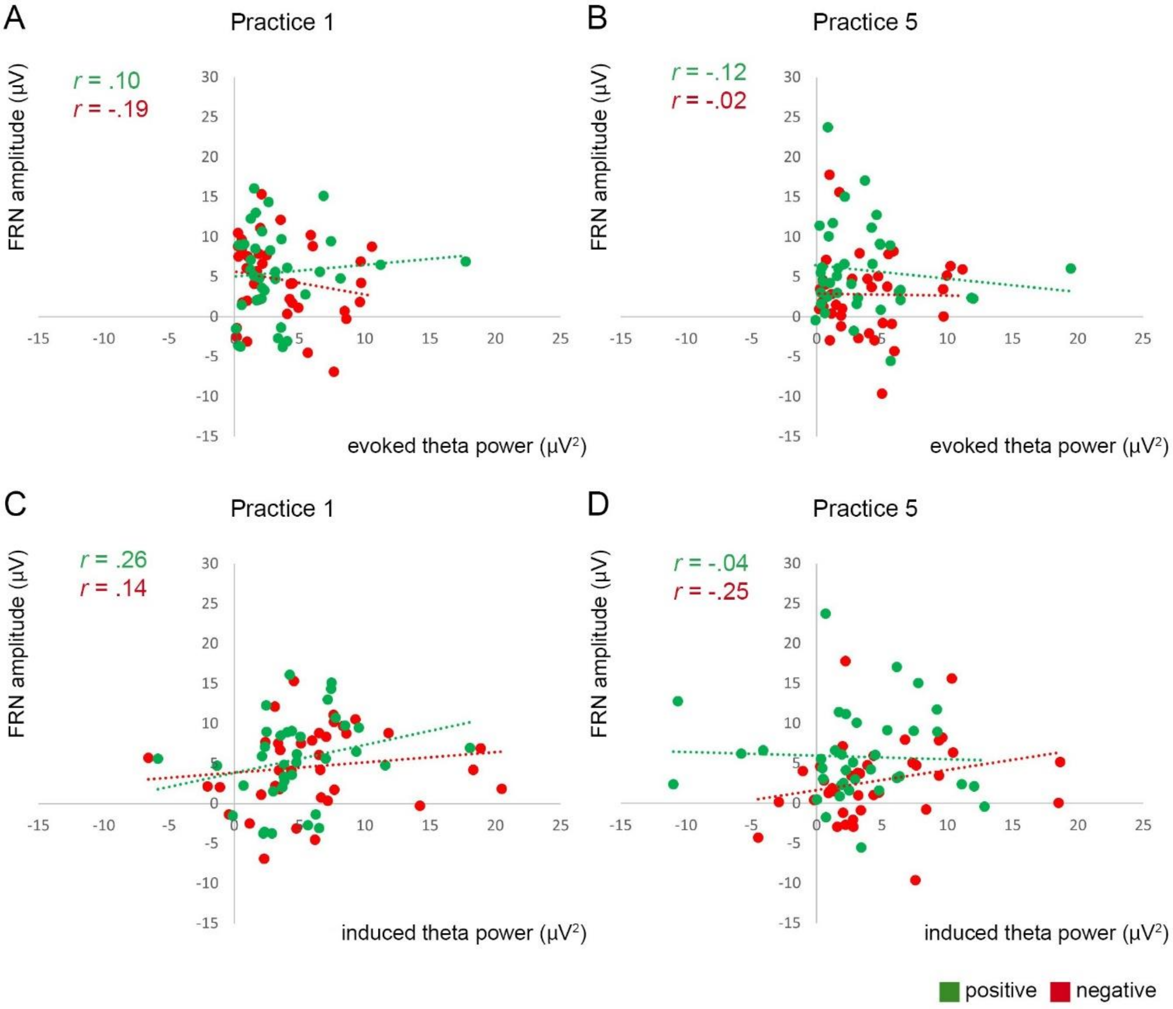
Correlations between Frontal Theta Power at the FCz and the ERPs

	Practice 1			Practice 5		
	r	*p*	*p*[1]	*r*	*p*	*p*[1]
FRN: Evoked theta after positive feedback	.10	.572	>.999	-.12	.488	>.999
FRN: Evoked theta after negative feedback	-.19	.267	>.999	-.02	.929	>.999
FRN: Induced theta after positive feedback	.26	.128	.512	-.04	.808	>.999
FRN: Induced theta after negative feedback	.14	.409	>.999	.25	.143	.572
LFCP: Evoked theta after positive feedback	.25	.131	.524	.50	.002	.008
LFCP: Evoked theta after negative feedback	.24	.151	.604	.46	.005	.020
LFCP: Induced theta after positive feedback	.42	.010	.040	.09	.584	>.999
LFCP: Induced theta after negative feedback	.58	<.001	.004	.50	.002	.008

Note: The FRN was quantified as the mean activity ± 20 ms around the peak amplitude in a time window of 230 to 350 ms after feedback onset. The LFCP was quantified as the mean activity ± 20 ms around the peak amplitude in a time window of 450 to 550 ms after feedback onset. [1]Based on multiple comparions the p-values were Bonferroni-Holm corrected.

Figure 4

Correlations of Frontal Theta Activity and Amplitudes of the FRN at the FCz Electrode



Note: (**A**) Correlations between FRN-amplitudes and evoked (phase-locked) theta power for positive (green) and negative (red) feedback in Practice 1. (**B**) Correlations between FRN-amplitudes and evoked (phase-locked) theta power for positive (green) and negative (red) feedback in Practice 5. (**C**) Correlations between FRN-amplitudes and induced (non-phase-locked) theta power for positive (green) and negative (red) feedback in Practice 1. (**D**) Correlations between FRN-amplitudes and induced (non-phase-locked) theta power for positive (green) and negative (red) feedback in Practice 5.

Appendix

A| 1 Methodological Issues of Time-Frequency Analysis

A| 1.1 The Time-Frequency Trade-off

The time-frequency trade-off refers to the relation between time-resolution and frequency-resolution (Cohen, 2014). The time-resolution relates to the accuracy of the identification of the time-point, while the frequency-resolution relates to the accuracy of the identification of the frequency-band. The time-frequency trade-off states that a better resolution in the frequency-domain implies a poorer resolution in the time-domain, and vice versa (Cohen, 2014; Leuchs, 2019). During the analysis, the time-frequency trade-off can be modulated by the Morlet parameter c, which defines the number of cycles of a wavelet (the length of the wavelet) (Leuchs, 2019). Shorter wavelets provoke a better time-resolution, while longer wavelets result in a better frequency-resolution (ibid.). How many cycles should be used depends on the goal of the analysis. If the goal were to depict changes in neural activity across the length of the segment, fewer cycles should be used (3 – 4) (ibid.). However, if the goal was rather to examine distinct frequency-band activity across a longer time-period, more cycles are recommended (7 – 10) (ibid.). The default of the Brain Vision Analyzer is set to 5. With respect to the current study, it helped to predefine a frequency-band of interest, which was the theta-frequency band. However, the result that reflects the theta-frequency range best, in terms of separability from other frequency-bands by providing a relatively clear time range of occurrence, was the Morlet Parameter 6.

A| 1.2 The Power Law (1/f phenomenon)

The next issue that should be considered is a phenomenon called the power law (1/f). This phenomenon refers to the power scaling of a time-frequency-spectrum (Cohen, 2014). The scaling that fits well with one frequency-band might be poor for another frequency-band, higher or lower. With respect to the power law, the frequency spectrum shows increased power for the lower frequencies and decreased power for the higher frequencies (ibid.). This phenomenon implies some limitations with respect to time-frequency data (ibid.). First, it is difficult to compare several frequency-bands depicted on the same frequency plot with each other. Second, the statistical comparison across different frequencies is not possible. Third, the separation of task-related activity and background noise is difficult. There are some methods of baseline normalization that address this phenomenon, these will be discussed below.

A| 1.3 Border and Smearing Effects, and Baseline Normalization

Border and smearing effects are another issue that should be taken care of when analyzing time-frequency data (Leuchs, 2019). Border effects refer to distortions at the segment's borders; smearing effects refer to overlapping of the post-stimulus interval and the pre-stimulus interval related to the next trial (ibid.). Border effects need to be considered when choosing the baseline interval for data normalization. Smearing effects should be considered when choosing the time between trials.

The influence of pre-stimulus background activity that was not event-related should also be reduced in time-frequency analysis (as with ERP analysis). This process is called baseline normalization (Cohen, 2014; Leuchs, 2019). Further, some baseline normalization methods also help with handling the underlying power law (as described above) and enable a comparison across frequencies (Cohen, 2014). But baseline normalization in time-frequency analysis is not as simple as for baseline correction in ERP analysis as a larger number of methods exist (Grandchamp & Delorme, 2011), all of which re-scale the data and, therefore, may change the data and the interpretation (Cohen, 2014). There are two main aspects to be considered: First, the question of whether the baseline normalization method should be applied to averaged data or to single-trial data. Second, the question of whether the baseline normalization method should be based on a division or on a subtraction.

Related to the first question, single-trial baseline correction methods are less sensitive to noise and outliers as compared to baseline correction based on averaged data (Grandchamp & Delorme, 2011), although the influence of especially large outliers cannot always be prevented (Cohen, 2014). However, with respect to time-frequency data, single-trial baseline normalization is more recommended than averaged baseline normalization (Grandchamp & Delorme, 2011). The second question related to the calculation method is not only a methodological question but also a matter of interpretation of the data. There are two assumptions of how neural activity are related to each other before and after the onset of a stimulus or an event (e.g., Grandchamp & Delorme, 2011; Gyurkovics et al., 2021). First, event-related activity may be defined as an increase or decrease of activity in relation to the baseline activity. That is, no new neural response was provoked by the event or the stimulus, instead, the event or the stimulus changes the pre-existing neural activity (Gyurkovics et al., 2021; Hu et al., 2014). In this case, event-related activity depends on the baseline activity. Second, event-related activity was added to or subtracted from the baseline activity. The event or the stimulus provokes a new neural response that was independent from the baseline activity (ibid.). Methods for baseline normalization that rather support the first assumption are based on a division; methods that predominantly support the second assumption are based on a subtraction.

Methods based on a division are, for example, the normed output (the data is divided by the mean of the reference interval), the percentage change (re-scaling to the reference interval expressed as a percentage), the decibel conversion (re-scaling to the absolute mean of the reference interval expressed on a logarithmic scale), and the z-transform (re-scaling to the standard deviation within the reference interval) (Cohen, 2014). These methods have the advantage that they overcome the power law (1/f) and, therefore, enable a comparison across frequencies (ibid.). But notably the decibel conversion should not be applied to single-trial data because the calculation of the log-transform tends to lead some values toward the infinite if the value is too close to zero, these trials would dominate the frequency spectrum (Grandchamp & Delorme, 2011). In relation to subtraction-based baseline normalization, it should be considered that this method does not resolve the power law (1/f), accordingly, no comparison across different frequencies is possible (e.g., Cohen, 2014). However, even though the decibel conversion is one of the most commonly used methods (ibid.), single-trial baseline normalization based on a subtraction is also recommended (Grandchamp & Delorme, 2011; Hu et al., 2014).

With respect to the current study, a baseline normalization method that was robust against outliers was preferred. Moreover, an additive connection of baseline activity and event-related activity seems more likely than a multiplicative connection (Gyurkovics et al., 2021). The assumption of a multiplicative connection bears the risk that a falsely assumed correlation of baseline activity and event-related activity may distort the data (ibid.). However, a single-trial baseline normalization based on the subtraction appears to be the most reasonable in the current study. As the study focused solely on the theta-band activity and did not aim to compare different frequency-bands, the power law (1/f) should not be a problem.

Another difference related to baseline correction in ERP analysis and baseline normalization in time-frequency analysis is the choice of the baseline interval. In ERP analysis, it is recommended to use a pre-stimulus interval with a duration of at least 20% of the duration of the whole segment (Luck, 2014). The baseline-interval usually starts some hundred milliseconds before the event and ends with event onset (ibid.). However, this recommendation did not apply to time-frequency analysis because of border and smearing effects (Leuchs, 2019). The baseline interval should end some hundred milliseconds before onset of an event to prevent post-stimulus activity being contained in the baseline activity (due to border effects) (Cohen, 2014; Leuchs, 2019). Further, the baseline interval should not be so far ahead from the stimulus onset that post-stimulus activity related to the previous trial was included (smearing effects).

Another aspect concerning baseline correction or normalization in time-frequency analysis is the question whether both baseline correction in the time-domain and a baseline normalization in the frequency-domain should be applied to the data. Unfortunately, no clear answer was found here in the literature. However, Herrmann and colleagues (2014) recommend a baseline correction in the time-domain before calculating the wavelet transform to prevent artifacts provoked by the ERP. In the current study, both pre-processing pipelines (with baseline correction in the time-domain, without baseline correction in the time-domain) were compared with respect to the valence- and practice-related analyses related to the FCz electrode. With respect to evoked theta activity, the 2 x 2 ANOVA revealed comparable effects for both pre-processing pipelines. Concerning induced theta activity, the 2 x 2 ANOVA revealed approximately the same effects, the practice effect fell just out of significance (p = .051; η^2_p = .10). When looking at the mean values calculated for the frontal electrodes, in most cases there was no significant difference between both preprocessing pipelines. It is recommended to compare the results of both pre-processing pipelines again more precisely and statistically in more detail. But this was beyond the scope of the current study. With respect to the current data, it was chosen to perform a baseline correction in the time-domain before calculating the wavelet transform, as was recommended by Herrmann and colleagues (2014).

A|1.4 Frequency Range

The last important decision during the analysis concerns the frequency-range to be analyzed, that is to define the minimum frequency (in Hz) and the maximum frequency. The first thing to note here is that a frequency-range from about 1 Hz up to 150 Hz are discussed related to cognitive processes and, consequently, are most frequently found in the literature (Cohen, 2014). To avoid low frequency noise, the minimum frequency should be set to 1 Hz (delta frequency-band, 1 – 3 Hz). With respect to higher frequencies, the sampling rate during recording defines the fastest frequency-band that can be detected (ibid.). The highest frequency that can be measured corresponds to half of the sampling rate of the data (Nyquist theorem) (ibid.). This is because at faster frequencies, the cycles cannot be picked up by the sampling rate. Frequencies above the Nyquist, therefore, are measured as slower than they are. But, in general, there is no need to analyze the highest frequency possible, the choice of the maximum frequency should depend on the frequency range of interest (ibid.). If one is not especially interested in the gamma-frequency band (above 35 Hz), it is usually enough to set the limit at 30 Hz (beta-frequency band, 15 – 30 Hz).

A| 2 Selected Aspects of Neural Measurements

A| 2.2 Quantification of ERP-components

The last step of EEG data processing is to define a suitable quantification of the ERP-components. That is, the values that are included in the statistical analysis. An ERP component is characterized by its polarity (positive or negative), its amplitude (size of the ERP, voltage given in microvolt, µV), and its latency (time after feedback onset in which the component appears, given in milliseconds; ms) (Luck, 2014). ERP quantification approaches aim to find a measurement of the size and the timing of the ERP component, with minimal noise or overlap from other components (ibid.). There are several options to do so (e.g., mean area, peak amplitude, peak-to-peak). What all methods have in common is that all of them require a defined time window in which the component is assumed to appear (ibid.).

Before explaining the different approaches for quantifying ERP components, the problem of trial-to-trial variability within the EEG data will briefly be addressed. While the variability of the amplitudes from trial-to-trial is not a problem in most cases, the variability of the latency can be very problematic, especially for later components (cf., Luck, 2014). A wide range of latencies can cause the mean amplitudes to appear flatter than they are. This is especially problematic if the variability of the latencies differs between different conditions. It could cause the data to show variations between conditions that are not actually present. This problem should be considered when quantifying ERP-components.

Next, different approaches for quantification will be briefly explained and subsequently discussed regarding the current data. The two most common methods are the peak amplitude and the mean amplitude (Luck, 2014) The peak amplitude is the point of the highest voltage within a defined time window. The mean amplitude is calculated as the average amplitude over a defined time window. It is usually recommended to calculate the mean amplitude rather than the peak amplitude (ibid.). This is because the peak amplitude is very susceptible to outliers, which would be relativized by the mean amplitude. Another problem with the peak amplitude is that the highest voltage within a defined time window does not always identify the peak of a component but bears the risk of marking a point at the edge of the defined window that belongs to the slope of a following component with a higher amplitude.

Related to the current study, the mean amplitude (defined as the average voltage over a defined time window) was not felt to be the appropriate method to quantify the ERP-components of interest. The time course of neural processing was very heterogeneous between participants. To include all participants' ERP-components of interest in the grand average, the chosen time windows defined for the mean amplitude would have to be relatively large. These larger time windows combined with the temporal variability of neural processes across participants was assumed to increase the risk of overlapping components in the calculation of the mean amplitude. Therefore, the peak amplitude was thought to be the more suitable method. To prevent identification of that the wrong maximum voltage (a point at the edge of the time window that belongs to the slope of a subsequent component) rather than the peak amplitude, the local peak amplitude was identified. The local peak amplitude is defined as "*the largest point in the measurement window that is surrounded on both sides by lower voltages*" (Luck, 2014, p. 285). Further, to reduce the impact of outliers, a mixture of mean amplitude and local peak amplitude was used for quantification. The ERP components in the current setting were defined as mean amplitudes of a defined time window (±20 ms) surrounding a detected local peak in the defined time window. This way of quantification was also recommended by Williams and colleagues (2021) who compared different methods ('mean amplitude', 'maximum peak', and 'base-to-peak') of quantifying the reward positivity.

However, they defined the mean amplitude as the average of the voltage surrounding a detected peak. For the sake of completeness, the base-to-peak measure was defined as the subtraction of the minimum voltage of the trough immediately prior to the maximum voltage of the ERP component (Williams et al., 2021). Williams and colleagues recommend handling the base-to-peak measure with caution, as it is not suitable for isolating the FRN/rewP component, but it does highlight differences between the P200 and the N200.

Another point of quantification concerns the waveforms of the ERPs. ERP-components are often isolated by the calculation of difference waves. This means, the waveform elicited by a trial of one condition is subtracted from the waveform elicited by a trial of another condition. This method highlights the difference in neural processing between experimental conditions and eliminates neural processes that did not differ between conditions (Luck, 2014). However, related to the current study, it was suspected that this method blurred the neural processes related to each condition rather than highlighting the variations. This assumption was based on the ambiguous feedback design in which quantitative error information was transported with both feedback conditions (negative and positive). As a result, the positive feedback display also contains quantitative error information, which might also be interpreted as negative performance outcome. Therefore, it was chosen to conduct statistical analyses based on the valence-dependent waveforms.

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Declaration of Authorship

I have read, understood, and accepted the PhD regulations (“Promotionsordnung der Fakultät für Naturwissenschaften an der Universität Paderborn vom 31. März 2021”).

I hereby formally declare that I have written this dissertation independently and that I have indicated all sources and auxiliary materials to the best of my knowledge and belief. Text passages taken over verbatim or in content are designated as such. Support during the research process and co-author contributions are presented for each publication.

The present dissertation has not been submitted for any degree or qualification at another university and has not yet been submitted anywhere for examination.

Erklärung der Autorenschaft

Ich habe die geltende Promotionsordnung (“Promotionsordnung der Fakultät für Naturwissenschaften an der Universität Paderborn vom 31. März 2021”) gelesen, verstanden und akzeptiert.

Hiermit erkläre ich förmlich, dass ich diese Dissertation eigenständig verfasst habe und alle Quellen und Hilfsmittel nach bestem Wissen und Gewissen angegeben habe. Textstellen, die wörtlich oder inhaltlich übernommen wurden, sind als solche gekennzeichnet. Unterstützung während der Forschung und Beiträge der Ko-Autoren sind für jede Publikation angegeben.

Die vorliegende Dissertation wurde nicht für einen Abschluss oder eine Qualifikation an einer anderen Universität eingereicht und hat noch an keiner anderen Stelle zur Prüfung vorlegen.

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