



Learning to throw: Contributions of contextual interference and individual differences

to the acquisition of a complex motor skill.

An investigation with event-related brain potentials.

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von Dipl.-psych. Romy Frömer

Prof. Dr. Jan-Hendrik Olbertz
Präsident der Humboldt-Universität zu
Berlin

Prof. Dr. Richard Lucius
Dekan der Lebenswissenschaftlichen
Fakultät

Gutachter/Gutachterin

1. Prof. Dr. Werner Sommer
2. Prof. Dr. Birgit Stürmer
3. Prof. Dr. Clay Holroyd

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Lehrstuhl für Biologische Psychologie und Psychophysiologie
Institut für Psychologie
Lebenswissenschaftliche Fakultät
Humboldt-Universität zu Berlin
Unter den Linden 6
10099 Berlin

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Table of Content

Abstract	1
Zusammenfassung.....	2
Synopsis	3
1. Introduction	3
1.1. A theory of motor learning and influential factors	4
1.2. Electrophysiological correlates of motor learning.....	9
1.3. Aims and outline of the present work	15
2. Summary of the present studies.....	17
2.1. Effects of reasoning abilities and CI on skill acquisition (Study 1)	17
2.2. CI and differential learning effects on ERP components (Study 2).....	18
2.3. Graded Positive Performance Feedback and Reward Positivity (Study 3).....	21
3. General discussion and future directions.....	24
3.1. Schema formation, CI and variability of practice in parameter learning.....	24
3.2. CI, cognitive load and the two processors in motor learning	26
3.3. ERP correlates of motor learning and the locus of the CI effect	28
3.4. Conclusions.....	30
References	31
Original Articles.....	43

Abstract

The acquisition of motor skills is influenced by several factors. Feedback, training schedule and individual differences between learners are three of them and were investigated in the present thesis. A special focus was on brain processes underlying feedback processing and motor preparation. These were investigated using event related potentials (ERPs). In a large study, we trained 120 participants to throw at virtual targets and tested them in a subsequent session for retention and transfer. ERPs were recorded in both sessions. Training schedule was manipulated with half of the participants practicing under high contextual interference (CI) (randomized training) and the other half under low CI (blocked training). In a follow-up online study, 80% of the participants completed a subset of the Raven advanced progressive matrices, testing their reasoning ability. We could show, that under high CI, participants' reasoning ability was related to higher performance increase during training and higher subsequent performance in retention and transfer. Similar effects of reasoning ability on performance increase in late stages of low CI training indicate, that variability is a necessary prerequisite for beneficial effects of reasoning ability. We conclude, that CI affects the amount of variability of practice across the course of training and thereby modulates whether learning is rule-based or pattern-based (Study 1). This interpretation is fostered by findings of differential learning effects on ERPs in the preparatory phase. High CI shows a larger decline in attention- and control-related ERPs than low CI. Moreover, CNV amplitude, as a measure of motor preparatory activity, increases with learning only, when attention demands of training and retention are similar, as in low CI training. This points to two parallel mechanisms in motor learning, with a cognitive and a motor processor, mutually contributing to CNV amplitude (Study 2). In the framework of the "reinforcement learning theory of the error related negativity", we showed, that positive performance feedback is processed gradually and that this processing is reflected in varying amplitudes of reward positivity (Study 3). Together these results provide new insights on motor learning.

Zusammenfassung

Feedback, Trainingsplan und individuelle Unterschiede zwischen Lernern sind drei Faktoren die den motorischen Fertigkeitserwerb beeinflussen und wurden in der vorliegenden Dissertation untersucht. Ein besonderer Fokus lag auf den zugrundeliegenden Gehirnprozessen von Feedbackverarbeitung und Handlungsvorbereitung, die mittels ereigniskorrelierter Potenziale (EKPs) untersucht wurden. 120 Teilnehmer trainierten auf virtuelle Zielscheiben zu werfen und wurden in einer Folgesitzung auf Abruf und Transfer getestet. In beiden Sitzungen wurden EKPs aufgezeichnet. Der Trainingsplan verursachte entweder hohe contextual interference (CI) (randomisiert) oder niedrige CI (geblockt). In einer anschließenden Onlinestudie, bearbeiteten 80% der Teilnehmer eine Untermenge der Raven advanced progressive matrices, die schlussfolgerndes Denken (SD) erfassen. Unter hoher CI hängt besseres SD mit größerem Zuwachs im Training und höherer Performanz in Abruf und Transfer zusammen. Ähnliche Effekte von SD im späten Trainingsverlauf unter niedriger CI lassen darauf schließen, dass Variabilität eine notwendige Voraussetzung für positive Effekte von SD ist. Wir folgern, dass CI das Ausmaß an Praxisvariabilität über den Trainingsverlauf beeinflusst und darüber moduliert, ob Lernen regelbasiert oder musterbasiert erfolgt (Studie 1). Diese Interpretation wird durch differenzielle Lerneffekte auf EKPs in der Vorbereitungsphase gestützt. Hohe CI führt zu einer stärkeren Abnahme von aufmerksamkeits- und kontrollbezogenen EKPs während der Vorbereitungsphase. Darüber hinaus nimmt die CNV Amplitude, als Maß motorischer Vorbereitungsaktivität zu, allerdings nur, wenn die Aufmerksamkeitsanforderungen in Training und Abruf gleich sind, wie bei niedriger CI. Das spricht für zwei parallele Mechanismen motorischen Lernens, die gemeinsam zur CNV Amplitude beitragen (Studie 2). Wir zeigten außerdem, dass sich graduelle Verarbeitung positiven Performanz-Feedbacks in der Variation der Amplitude der Reward Positivity widerspiegelt (Studie 3). Zusammen geben diese Ergebnisse neue Einsichten in den motorischen Fertigkeitserwerb.

Synopsis

1. Introduction

The acquisition and refinement of motor skills is a fundamental part of human life. Early studies on factors influencing motor learning mainly used simple actions, such as choice reaction time tasks, time estimation tasks or artificial movement sequences. It is not surprising that some mechanisms and principles derived from such research did fail, when investigated in more complex applied settings. Whereas in simple tasks, under low cognitive load, frequent feedback or support might interrupt learning, in complex tasks with higher cognitive load, it aids skill acquisition, by reducing the load (Wulf & Shea, 2002). Similarly, a demanding schedule with high contextual interference (CI), randomly practicing several movements, is advantageous for the acquisition of simple skills, but detrimental to the acquisition of complex skills (Barreiros, Figueiredo, & Godinho, 2007). As load appears to be an important factor mediating the effects of other variables in training, individuals' capacity should be relevant for the effectiveness of such experimental manipulations.

The present thesis elucidates effects of contextual interference and individual differences in reasoning ability on skill acquisition using a complex motoric task, throwing. Specifically, effects of reasoning ability on skill acquisition were investigated within high and low CI (Study 1). Moreover, effects of CI on learning related changes in ERPs during the motor preparatory stage were examined (Study 2). Furthermore, we zoomed in to the basic level of feedback processing, as a substantial factor in skill acquisition (Study 3). I will introduce a theory of motor learning and influential factors (Section 1.1). Subsequently I will present the corresponding ERPs (Section 2.2) to then outline the aims of the present work (Section 1.3). The present studies will be summarized in Section 2 and jointly discussed in Section 3.

1.1. A theory of motor learning and influential factors

In the following section, I will introduce models on motor skill acquisition and control (Section 1.1.1), as well as variables influencing this process. Thus I will review literature on effects of training schedule (Section 1.1.2), as well as individual differences and skill acquisition (Section 1.1.3). Finally, I will introduce the reinforcement learning theory, which centers on outcome evaluation supporting skill acquisition (Section 1.1.4).

1.1.1. Schmidt's Schema Theory. An influential theory of motor learning is Schmidt's Schema Theory (Schmidt, 1975). It proposed that classes of movements are represented as generalized motor programs (GMPs), as distinct representation of every single movement would easily surpass storage capacity. GMPs cover invariant features of classes of movements that are parameterized to the current needs of a specific task. This assumption also takes into account, that movements are often executed quickly, and that some movements, such as ballistic movement do not allow for online control, but must be prepared in advance. Preparation of a movement includes specification of the GMP and parameterization. Parameters are derived from schema information. Schemata contain abstract representations of response – outcome rules. Schmidt distinguishes between two kinds of schemata: *recall schemata*, holding parameter specification-outcome rules and *recognition schemata*, integrating proprioceptive and external sensory information and outcome information. Whereas recall schemata are used for response production, recognition schemata are more relevant for response evaluation. For movements of the same class, the abstract representation of parameter specifications and outcomes in the corresponding recall schema allows for transfer to new movements, never executed before. Hence, when you throw a basketball, you can do this from a lot of different positions without training every single one separately. The more different positions you learn to throw from, the higher is the variability of practice, which is defined as the performance of multiple variants of the same class of movements. During skill acquisition, variability of practice aids schema formation, as it

enhances the amount of information to be abstracted to the schema. In this way, representations of schema rules are strengthened. The stronger the schema, the better is transfer performance to novel tasks of the same class.

Schmidt's schema theory was criticized for its inability to explain practice order effects, that is effects of the organization of tasks within training (Merbah & Meulemans, 2011; Newell, 2003; C. H. Shea & Wulf, 2005). If it is only the amount of variants of a task performed, that counts for the formation of schemata and the order of these experiences is irrelevant, no effects of practice order should be observed.

1.1.2. Contextual Interference. Contextual interference (CI) relates to the organization of training during skill acquisition and addresses above mentioned practice order effects. CI is high, when several tasks (or variants of a task) are practiced in close temporal proximity, as in randomized training and it is low, when tasks are learned in isolation, as in separate training blocks. In laboratory settings, high CI results in inferior performance in training than low CI, but to superior performance in retention and transfer (Brady, 2004; J. B. Shea & Morgan, 1979). Several theories attempt to explain the CI effect. The most prominent are the *elaboration hypothesis* (J. B. Shea & Morgan, 1979) and the *reconstruction hypothesis* (Lee & Magill, 1983). The elaboration hypothesis assumes that during high CI training, multiple action plans co-reside in working memory, where they are compared. This leads to more elaborate and complex representations of the action plans. In contrast, the reconstruction (or forgetting) hypothesis assumes that the motor solution process (finding the correct movement with regard to the goal) must be repeated in actively in every trial, when the condition changes. Thus, the action plan must be reconstructed instead of just rerunning it. This repeated problem solving results in stronger representations of the action plan.

For simple tasks there is converging evidence about the CI effect. In contrast, in applied settings and for complex tasks results are mixed (Barreiros et al., 2007; de Croock, van Merriënboer, & Paas, 1998; Fegghi, Abdoli, & Valizadeh, 2011; Stambaugh, 2011).

Albaret and Thon (1998) tested whether CI interacted with task complexity in a drawing task without visual control. Complexity was manipulated by varying the number of segments participants had to draw within a shape (between one and four). For the simple shapes there was a clear CI effect in retention and transfer, but not for shapes with more than two segments.

Wulf and Shea (2002) proposed that CI increases cognitive demands during acquisition. In simple tasks, this leads to intensified processing and as a consequence better retention and transfer. However, with increasing task complexity, cognitive demands accumulate potentially causing overload, which disrupts learning. This proposal points toward the assumption of an optimal load for learning, as proposed by cognitive load theory (CLT, Sweller, 1988). Sweller (1994) differentiates between exogenous cognitive load, produced by the learning environment, and endogenous cognitive load, stemming from within-task element interactivity (e.g. the relationship between segments to be drawn in a shape). Both accumulate in working memory and at a given threshold exceed its capacity. Consistently, in simple tasks, the CI effect is most stable when motor programs vary, that is when movements from different classes need to be learned. In contrast, in complex tasks with high element interactivity, the use of several motor programs exceeds capacity. Here the CI effect is more stable when parameters of the same motor program need to be learned (Merbah & Meulemans, 2011). This is consistent with the CLT assumption that element interactivity, which relates to the concept of variability of practice in Schema theory, drives schema formation. Schema formation in turn reduces intrinsic load (Paas, Renkl, & Sweller, 2003). Consistently, extended practice increases the efficiency of CI (C. H. Shea, Kohl, & Indermill, 1990). Moreover, participants with higher experience levels were found to profit from high CI (Hall, Domingues, & Cavazos, 1994), whereas novices show better performance after low CI training (Guadagnoli, Holcomb, & Weber, 1999; Hebert, Landin, & Solmon, 1996). CI works better for older children and adults compared with young children (Farrow & Maschette,

1997; Wulf & Shea, 2002), but only when adults and older children are more familiar with the tasks examined (Pinto Zipp & Gentile, 2010). Consistent with CLT, CI effects depend not only on task features, but also the learning stage, with high CI being detrimental in early learning stages.

1.1.3. Motor learning and individual differences in cognitive ability. From an individual differences perspective, Ackerman (1988) assumes three independent phases of skill acquisition. In the beginning, learning consists of hypothesis testing, which is related to declarative knowledge and, hence, dependent on cognitive resources, such as working memory. Once a solution is established, there is a transition to an associative phase, in which the relevance of cognitive abilities decreases and perceptual speed gets more important. Finally, once the skill is well established it becomes autonomous and independent of cognitive abilities, being governed by procedural memory and determined by psychomotor abilities (Ackerman & Cianciolo, 2000; Beaunieux et al., 2006).

Woltz (1988) has shown effects of working memory on the acquisition of a cognitive procedural task. Participants had to perform actions, depending on different conditions according to a complex set of rules, comparable to a monitoring task at a control panel. Whereas the learning stages in the acquisition of this skill might be the same, this cognitive task differs in two key aspects from motor skill acquisition. First, acquisition in this task was related to response selection, rather than response production. Other than here, in motor skill acquisition, usually the “what” is clear, but the “how” is not. Second, this study did not require the deduction of production rules because the rules were provided in advance. Contrary, in motor skill acquisition, relationships between movement characteristics and outcomes are hard to verbalize and multiple different parameter combinations can solve the same motor problem. Although results from the cognitive domain might transfer to the motor domain, to our knowledge, the relationship between cognitive abilities and performance in motor skill acquisition has not previously been tested.

As task complexity seems to modulate cognitive load (see section 1.1.2), it should mediate the effectiveness of cognitive abilities to predict motor learning. In the language domain, Opitz and Friederici (2003) showed that during learning of complex artificial grammars participants changed from similarity-based decisions to rule abstraction. For simple grammars, pattern-based learning was sufficient. Pattern-based learning is independent of declarative knowledge and can occur implicitly, that is without working memory involvement. The acquisition of rule knowledge, in contrast, requires explicit learning and both, pattern-based and rule based learning, take place under explicit learning conditions (Opitz & Hofmann, 2015). Transferring this to the motor domain, motor learning might require both, pattern-based learning of the associations between actions and their outcomes, as well as rule-based integrating a variety of action- and outcome information.

An important variable determining the ability to abstract trial-to-trial information to a unifying pattern is (inductive) reasoning (Heit, 2000). Earlier studies on effects of cognitive ability on learning relate to working memory, not reasoning. Still, reasoning ability covers the identification and use of patterns from a variety of sources and it is highly correlated with working memory (Buehner, Krumm, & Pick, 2005; Kyllonen & Christal, 1990; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002). In the framework of schema theory, reasoning ability should therefore be a suitable predictor for schema formation/ learning.

1.1.4. Feedback and reinforcement learning. Simple actions, like pressing the correct button in a two-choice task can be evaluated regarding goal achievement based on internal proximal afferent motor feedback. In contrast, when it comes to complex goal directed actions, external feedback on the distal effects of actions is required (Henderson, 1977; Wulf & Shea, 2002). In motor learning, external feedback on performance in relation to the goal, termed Knowledge of Results (KR) is a key variable and has been shown to improve performance (for a review see Salmoni, Schmidt, & Walter, 1984).

Reinforcement learning theory provides a framework how feedback is utilized in behavioral adaptation and learning (Sutton & Barto, 1998). Here, the actual outcome (feedback) is compared to the predicted outcome to trigger adaptation. Previous outcomes are the basis for predictions/expectations and the difference between actual outcome and the expectation is termed prediction error. In turn, the prediction error in a given trial is used to adjust the prediction of the outcome in subsequent trials and select responses in order to optimize performance. The size of the difference determines the magnitude of the prediction error. Take, as an example, someone who wants to learn basketball free throws. The learner will estimate the likelihood of making a goal based on his previous performance and generate a corresponding expectation. As long as his relative number of baskets is low, he will not expect to score a goal. Doing so would be a better-than-expected outcome (positive prediction error). Based on this new experience, the learner will adapt his expectation for the next trial, as scoring a goal is now more likely. This adaptation process is termed temporal difference learning. The reinforcement learning framework comprises two components: the critic that computes the prediction error, and the actor that selects actions that maximize the outcome by repeating successful behavior.

Consistent with the assumptions of reinforcement learning, processing of both, positive and negative feedback predicts behavioral adaptation and learning (Cavanagh, Frank, Klein, & Allen, 2010; Van Der Helden & Boksem, 2012). Beyond this, in some settings, positive feedback fosters learning to a larger extent than negative feedback (Arbel, Goforth, & Donchin, 2013; Arbel, Murphy, & Donchin, 2014; Chiviacowsky & Wulf, 2007; Eppinger, Kray, Mock, & Mecklinger, 2008; Wulf, Shea, & Lewthwaite, 2010).

1.2. Electrophysiological correlates of motor learning

I assume several processing stages during an action, which are schematically summarized in figure 1. The right side of the schema is related to preparatory activity in the dorsal and ventral visual stream, as well as the motor areas. The left side of the schema summarizes

stages related to behavioral adaptation and feedback processing. Relevant ERPs are displayed along with the corresponding processes.

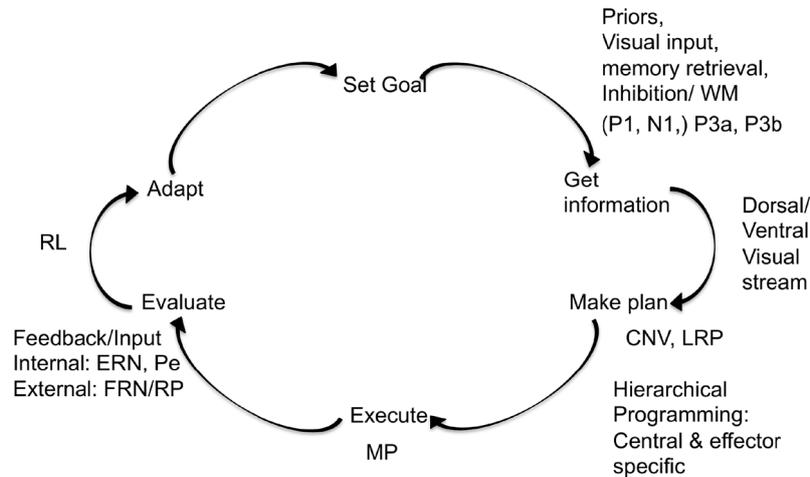


Figure 1: Schematic illustration of sub processes in motor control and learning with associated ERP components. CNV: Contingent Negative Variation, LRP: Lateralized Readiness Potential, MP: Motor Potential, ERN: Error related Negativity, Pe: Error Positivity, FRN: Feedback related Negativity, RP: Reward Positivity, RL: Reinforcement learning

The present outline will focus on preparatory activity, such as the extraction of motor relevant information from cues and the motor related preparatory activity (Section 1.2.1), as well as feedback related potentials in the framework of reinforcement learning (Section 1.2.2).

1.2.1. Preparatory activity and effects of learning. To investigate motor preparation independent of motor execution, S1-S2 paradigms are used. Here, a precue (S1), provides prior information on the required action. After a wait-interval (foreperiod) in which motor preparation can take place, an imperative stimulus (S2) prompts the action.

Information on the required action needs to be extracted from S1 prior to motor preparation. Part of this processing is reflected in the P3 component of the ERP. The P3 is a centrally distributed positive ERP with a maximum between 250 and 500 ms after stimulus onset. It can be separated into a more frontal component, the P3a, associated with allocation of focal attention, and a parietal component, P3b, related to memory operations (Polich,

2007). A selective decrease in the frontal component occurs with habituation to the task along with repetition and the frontal – parietal ratio is larger for more difficult tasks (Segalowitz, Wintink, & Cudmore, 2001).

The contingent negative variation (CNV), related to abstract motor preparation, is a slow cortical potential, starting on fronto-central recording sites and moving to more posterior sites with time (for a review see Leuthold, Sommer, & Ulrich, 2004). For foreperiods longer than 1 s the CNV can be separated into two independent waveforms, the early orienting wave or initial CNV (iCNV) with a fronto- central maximum and the following expectancy wave or late CNV (lCNV) with a centro-parietal maximum (Brunia & Damen, 1988; Verleger, Wauschkuhn, van der Lubbe, Jaskowski, & Trillenber, 2000). The iCNV is assumed to be rather stimulus related, supposedly reflecting unspecific allocation of attention to task relevant stimuli in order to provide optimal readiness for action. Still, it seems to contribute to motor preparation beyond a mere orienting reaction, indicated by event related desynchronization in the alpha frequency range contralateral to the cued hand (Bender, Resch, Weisbrod, & Oelkers-Ax, 2004). Bender and colleagues argued that this activity reflects early task related preparatory motor processes, presumably memory retrieval of a motor program. The lCNV is assumed to equal the readiness potential (RP) that precedes voluntary actions (e.g. Prescott, 1986). Beyond this interpretation, the component is also sensitive to stimulus expectation, motivation and effort (for a review see Brunia, 2004). In the context of motor control, the lCNV is interpreted as reflecting the number of pre-specified parameters (Leuthold & Jentsch, 2001; Leuthold et al., 2004; Wild-Wall, Sangals, Sommer, & Leuthold, 2003). Its amplitude varies with task difficulty (Frömer, Hafner, & Sommer, 2012) and is larger for novel, as compared to learned movement sequences (De Kleine & Van der Lubbe, 2011).

From studies investigating the temporal aspects of motor preparation (time preparation), it is known, that randomized and blocked designs lead to differential experimental effects. Whereas in a blocked design, short foreperiods lead to better

performance and larger CNV amplitudes than long foreperiods, the opposite pattern is observed in randomized designs (Müller-Gethmann, Ulrich, & Rinkenauer, 2003). Müller-Gethmann et al. argued that the predictability of the time of S2 presentation is influenced by blocked versus randomized presentation contexts. Similar effects have been reported for manipulations that were performed either block-wise or randomly within blocks. The commonly found effect that fully informative precues lead to larger ICNV amplitudes than partial precue information was reported for random, but not for blocked presentation schedules (Rose, Verleger, & Wascher, 2001; Van Boxtel, Van den Boogaart, & Brunia, 1993). Thus, the CNV is context sensitive and task scheduling interacts with other manipulations in their effect on its amplitude. As a consequence, task scheduling should have an impact on learning-related effects on motor preparation, too.

Motor learning is associated with a frontal-parietal shift (Sakai et al., 1998; Shadmehr & Holcomb, 1997; Toni, Krams, Turner, & Passingham, 1998). The reduction in frontal activity is supposedly related to automation and a decrease in working memory load (Jansma, Ramsey, Slagter, & Kahn, 2001). Preparatory motor activity increases with learning of goal directed actions (Sakai, Ramnani, & Passingham, 2002). Using EEG, Staines, Padilla, and Knight (2002) observed a decrease in the frontal P3 component, associated with processing of task related stimulus features and an increase of the negative component preceding the execution of the response, related to response preparation. The latter result is inconsistent with above-mentioned decreased ICNV for learned compared to novel movement sequences (De Kleine & Van der Lubbe, 2011). As outlined above, CNV is sensitive to presentation schedule. The discrepancy might hence result from an interaction of presentation schedule and learning related changes in motor preparatory ERP components.

Evidence on differential effects of presentation schedule on learning related changes in the motor preparatory phase comes from fMRI research. Cross, Schmitt, and Grafton (2007) identified differential effects of high and low CI training (see Section 1.1.2) on premotor and

motor areas, as well as sensori-motor integration areas with increased activity during high CI learning. Furthermore, superior and medial frontal gyri and right lateral occipital areas, as part of the fronto-parietal attention network were more active under high CI. The later effects are consistent with assumed higher cognitive demands of high CI training or more elaborate processing. As these results only refer to comparisons between early and late training, an open question is how schedule effects preparatory activity in retention compared to training.

1.2.2. Electrophysiological correlates of feedback processing. The “reinforcement learning theory of the error-related negativity” (RL-ERN) is an implementation of reinforcement learning theory (see Section 1.1.4) at the neural level (Holroyd & Coles, 2002). According to RL-ERN, the reward prediction error is reflected by phasic changes of activity in anterior cingulate cortex (ACC). Performance-monitoring activity in the ACC is computed either on the basis of external feedback or internal information obtained by the response itself (Bellebaum & Colosio, 2014; Holroyd & Coles, 2002; Holroyd, Nieuwenhuis, et al., 2004). If based on internal processes, ACC activity seems to be reflected in the ERN; if based on external feedback, error detection is reflected in the feedback-related negativity (FRN).

The FRN is a fronto-centrally distributed negative ERP with a maximum around 200 - 400 ms after feedback onset (Holroyd, Pakzad-Vaezi, & Krigolson, 2008). Typically, the FRN is determined as the difference wave between ERPs to feedback signals about incorrect and correct responses or between non-reward and reward signals. The FRN is larger for negative as compared to positive outcomes (Miltner, Braun, & Coles, 1997) and it is sensitive to both, utilitarian (reward/punishment) and performance feedback (Nieuwenhuis, Yeung, Holroyd, Schurger, & Cohen, 2004). It is interpreted as reflecting the reward prediction error (Holroyd, Nieuwenhuis, Yeung, & Cohen, 2003). Consistent with this interpretation, the FRN is context dependent, with amplitude to a specific outcome depending on alternative outcomes (Holroyd, Larsen, & Cohen, 2004; see Kujawa, Smith, Luhmann, & Hajcak, 2013 for divergent findings; Nieuwenhuis et al., 2005). Moreover, reward probability or reward

magnitude modulations of the FRN were observed to error- and correct-related feedback ERPs, but more consistently for the latter (Cohen, Elger, & Ranganath, 2007; Hajcak, Holroyd, Moser, & Simons, 2005; Hajcak, Moser, Holroyd, & Simons, 2006; Kreussel et al., 2012; Potts, Martin, Burton, & Montague, 2006; Potts, Martin, Kamp, & Donchin, 2011; San Martin, Manes, Hurtado, Isla, & Ibanez, 2010). Compared to negative feedback, positive feedback elicits ERPs that are larger in amplitude and of different polarity (Walsh & Anderson, 2012). The interpretation of the FRN reflecting the signed prediction error is supported by a recent meta-analysis (Sambrook & Goslin, 2015).

Variations of feedback values indicated that the FRN is related to goal achievement, as neutral and irrelevant feedback elicited similar FRNs as negative feedback (Band, van Steenbergen, Ridderinkhof, Falkenstein, & Hommel, 2009; Holroyd, Hajcak, & Larsen, 2006). Holroyd et al. (2008) introduced the feedback correct related positivity. They argued that the lack of a typical N2 to correct feedback was due to cancellation with an overlapping positivity, other than the P3 and related to performance monitoring. Recent fMRI findings also support the assumption of a reward positivity (RP). An increase in BOLD response in areas related to reinforcement learning was observed following positive but not negative feedback. This increase of activity was related to more positive ERP amplitudes (Becker, Nitsch, Miltner, & Straube, 2014). Because these and other recent findings suggest a different interpretation of the FRN difference wave, we will henceforth refer to feedback related ERPs as RP (Baker & Holroyd, 2011; Holroyd, Krigolson, & Lee, 2011; Kujawa et al., 2013; Lukie, Montazer-Hojat, & Holroyd, 2014).

The above-mentioned studies mostly rely on dichotomous feedback or reward delivery vs. omission. Still, evidence on reward magnitude effects suggests, that errors and rewards are not processed in a dichotomous way. Thus, in a gambling experiment with a fortune wheel, the reward positivity amplitude was larger for full (win/miss), as compared to near (narrow win/near miss) outcomes, indicating that the visual feedback was processed in a graded, not in

dichotomous fashion (Ulrich & Hewig, 2014). Evidence on graded error monitoring in the response-locked ERN has been provided with larger amplitudes for larger errors (Anguera, Seidler, & Gehring, 2009). Similar effects have been reported for feedback-related potentials. In a time estimation task, the exact timing was returned as feedback information with larger errors resulting in more negative reward positivity amplitudes (Luft, Takase, & Bhattacharya, 2014).

1.3. Aims and outline of the present work

Aim of the present work was to shed light on the cognitive processes during the acquisition of a complex motoric task. As reviewed above, hypotheses on the CI effect relate to processing load and working memory (Lee & Magill, 1983; J. B. Shea & Morgan, 1979). The failure of many studies using applied and complex tasks to show CI effects was explained by overload of the cognitive system (Wulf & Shea, 2002). This assumption has never been tested directly. Moreover, to our knowledge, there is only one study investigating the underlying neural mechanisms of the CI effect and this study is furthermore limited to changes during training, omitting retention (Cross et al., 2007). In addition, feedback processing, as an important stage in skill acquisition, has mainly been investigated using simple tasks, such as time estimation tasks. Moreover, studies on graded performance feedback are rare and focus on error feedback (Luft et al., 2014). We aimed at contributing to previous literature, by investigating neural correlates of processing graded positive performance feedback in a complex motor task.

To approach these questions, we conducted a large learning experiment, training 120 participants to throw at virtual targets with a Nintendo Wii remote controller. Training comprised three horizontal target positions (left, center, right). We manipulated a spatial parameter of an existing motor program (throwing in general), as CI effects are more stable with prior experience (Guadagnoli et al., 1999; Hall et al., 1994; Hebert et al., 1996; Pinto Zipp & Gentile, 2010) and for parameter adaptation tasks, compared to practicing multiple

MPs (Wulf & Lee, 1993, see Section 1.1.2). Participants were – based on separately tested darts throwing performance – matched to two training groups with equal average performance. The high CI group practiced the three target positions randomly and the low CI group block-wise. Both training groups performed 105 trials of each target position, as extended training supports the effectiveness of CI (C. H. Shea et al., 1990). In a follow up session, one week later, retention was assessed for one of the practiced target positions (center) and transfer was tested for a larger target distance. Electroencephalographic (EEG) activity was measured in both sessions. We had shown feasibility of EEG recordings using this setup in an earlier study (Frömer et al., 2012). In a follow up online study, 80% of the sample completed a reasoning ability test, consisting of a subset of the Raven advanced progressive matrices.

Based on this dataset, the present work investigated motor learning at three different levels: behavioral, individual differences and neural. In Study 1 we tested the assumption that individual differences in reasoning ability interact with training schedule, limiting the effectiveness of high CI training. Moreover, we focused on electrophysiological correlates of two stages in motor learning, which are motor preparation and feedback processing. In Study 2 we investigated the effect of CI on learning related changes in ERPs in the motor preparatory phase. Besides the two CNV waves, we focused on activity related to the fronto-parietal attention network, that has been highlighted in previous research as being sensitive to CI manipulations, supposedly indicating differences in cognitive load. Finally, in Study 3 we investigated the effect of graded positive performance feedback on RP amplitude. As the outcome prediction influences RP amplitude, we used a linear mixed models approach that allows for trial-by-trial control of corresponding measures.

2. Summary of the present studies

2.1. Effects of reasoning abilities and CI on skill acquisition (Study 1)

Variability of practice enhances the amount of information on action-outcome relationships and presumably facilitates schema formation (Schmidt, 1975). Crucially, schema formation can be facilitated by variability only, if participants are able to abstract from the current task and integrate different learning occasions. Reasoning ability should determine whether individuals are able to abstract the relevant information to the underlying rule and learn. CI enforces the abstraction of underlying rules, as a consequence of higher temporal proximity of task variations but also increases load, which in addition to intrinsic load of complex tasks might encompass individual's capacity (Young, Cohen, & Husak, 1993). Study 1 investigated the effect of CI and individual differences in reasoning on skill acquisition to test the assumption, that effectiveness of CI is limited by processing capacity. We separately analyzed training and follow up performance using linear mixed models (LMMs). Although we considered factors influencing the CI effect in our design (large number of training trials, pre-learned MP, parameter adaptation, see section 1.1.2 and 1.3) we found no significant main effects of CI on performance, neither in training, nor retention and transfer. Even by the end of training and after significant improvement, mean performance was rather low (around 50% hits), indicating that difficulty was too high for CI to show overt beneficial effects. Learning took place mainly during the first third of training in both groups. As predicted, in the high CI group there was a significant main effect of reasoning with performance increasing with reasoning ability. In the first third of training, there was a tendency for steeper acquisition curves for participants with higher reasoning ability. A main effect of reasoning was present from the second third of training onwards, and persisted across retention and transfer. This finding is consistent with reports from the cognitive procedural skill acquisition domain (Ackerman, 1988; Ackerman & Cianciolo, 2000; Woltz, 1988). In contrast, for the low CI group, there were no main effects of reasoning at any stage of training or follow up. Still, in

the last third of training with increased variability of practice, there was a significant interaction of acquisition curve and reasoning. Thus, participants with higher reasoning improved more during this last stage of training. We interpret this result as a change from pattern- or association-based learning to rule-based learning or schema formation. That means, to our understanding, in the beginning of training, the low CI group performed the task pattern- or association-based, but switched to rule-based learning, once enough variability was provided. At that point, reasoning ability could show advantageous effects, but not previously. In summary, there was an effect of reasoning ability on performance improvement that was different in timing for the CI groups and showed persistent effects only for high CI. In other words the advantage of high reasoning seems to develop when there is variability of practice and persists, when variability of practice is introduced early.

Motor skills are often considered as independent from cognitive ability, as mainly governed by procedural learning and memory. Our study provides evidence, that at least the acquisition of motor skills is facilitated by higher cognitive ability and so is transfer within the same class of movements. Crucially, this effect only emerges, when sufficient variability of practice is given, allowing for the integration of information from multiple task variants to underlying rules. These findings propose a new perspective on CI, potentially reconciling CI effects and schema theory.

2.2. CI and differential learning effects on ERP components (Study 2)

As described in Section 1.2.1 motor learning is accompanied by a frontal-parietal shift in preparatory activity. CI influences the recruitment of brain regions in the preparatory phase of motor learning. Moreover, results on learning related changes in motor preparatory ERPs are heterogeneous and might be explained by task scheduling, as manipulated in CI. To systematically test this, in Study 2 we investigated the effect of CI on learning related changes in preparatory ERPs. Preparatory activity in training was compared to preparatory activity in retention, using the same condition. Specifically, the P3, iCNV and ICNV were analyzed. In

addition frontal and right lateral occipital activity in the two CNV time windows were analyzed, to assess, whether reductions in this activity are limited to cue related activity or persist throughout the preparatory interval, possibly reflecting a reduction in ongoing cognitive control. As expected, P3 amplitudes were reduced in retention for both groups. This finding is consistent with an interpretation of a reduction in frontal P3 activity as a decrease in ongoing cognitive control (Segalowitz et al., 2001). High CI resulted in reduced prefrontal activity throughout the whole foreperiod in retention relative to training. Supposedly part of the same attention network, right lateral occipital activity was larger during high CI training than during retention. These effects were specific to high CI training and not found for low CI training. The results are consistent with earlier findings on the recruitment of different brain structures depending on CI (Cross et al., 2007). This selective effect is consistent with the interpretation of enhanced effort under high CI (Young et al., 1993). In separate analyses of between group differences within training and retention, none of the components showed significant group differences in retention and only right lateral occipital negativity was significantly larger for high compared to low CI during training, indicating higher attention demands under high CI training. From previous literature, we expected larger CNV amplitudes in retention, as compared to training. We observed differential effects of the training schedule on CNV in retention, both in iCNV and ICNV. Whereas there were no effects on iCNV after low CI training, congruent with our hypothesis, however, ICNV was significantly increased. In contrast, high CI training led to a significant decrease in iCNV and a trend for a decrease in ICNV during retention relative to training. These results are consistent with previous findings that the CNV is larger in more difficult tasks (Frömer et al., 2012), and in unfamiliar tasks (De Kleine & Van der Lubbe, 2011). Whereas there were no significant differences between groups during training, ICNV was significantly larger during retention after low CI than high CI training. No differences were found for iCNV. Our results support previous interpretations suggesting that processes in addition to mere motor

programming affect the ICNV. Such factors cover motivation, stimulus anticipation, working memory and cognitive effort (Brunia, 2004; Ruchkin, Canoune, Johnson, & Ritter, 1995; van Boxtel & Brunia, 1994; Wascher, Verleger, Jaskowski, & Wauschkuhn, 1996). The latter two factors might explain the differences in retention effects between high and low CI training. Whereas working memory and attention demands are similar after low CI training, cognitive load in retention is significantly lower than during high CI training. A potential increase in the motor related portion of the ICNV, as observed after low CI training, might be masked by the proportionally stronger decrease in the effort related portion of the component. This interpretation is consistent with the assumption of two motor processors, as proposed by Verwey (2001). According to this model, a cognitive processor and a motor processor contribute to motor control in parallel. Whereas load on the cognitive processor decreases with learning, contributions of the motor controller increase. We propose that both processors are reflected in ICNV amplitude and that their interplay explains the differential effects.

P3, iCNV, as well as early frontal activity were significantly smaller in amplitude for hits as compared to misses, in the high CI group, only. A similar effect was observed for ICNV. Again, successful performance was related to smaller amplitude. Whereas it is unreasonable to assume that less effortful processing should result in superior performance, it is plausible that effort is reduced once the task is learned. Crucially no such effects were found for the low CI group. We interpret this finding as reflecting a stronger reduction in cognitive effort under high CI with increasing performance during and after learning. As the cognitive motor controller seems to be less active under low CI, performance does not affect load-related components.

Motor learning results in a decrease in cognitive demand, as reflected by a reduction in P3 amplitude in the preparatory period. High CI results in higher cognitive load during training and a stronger subsequent reduction in effort-related activity under retention. Motor preparatory activity increases during retention, but only if training and retention use a blocked

schedule. This effect is supposedly related to parallel cognitive and motor processing, both probably reflected in ICNV amplitude. Decrease in cognitive processing might overshadow an increase in motor preparation following high CI training. Future research needs to determine, whether the dependency of motor preparatory-related changes on training schedule are caused by different learning mechanisms, such as rule vs. pattern based learning during training.

2.3. Graded Positive Performance Feedback and Reward Positivity (Study 3)

In motor learning, graded feedback is related to better performance than dichotomous feedback relative to a standard, as this kind of feedback allows for more flexible goal-setting and hence improvements (Locke, 1968). If the outcome is evaluated based on goal attainment only, no further improvement is possible. Still, people do refine their skills, hence even successful actions should be processed in a graded fashion. As previous research focused on the processing of error feedback, aim of Study 3 was to investigate whether gradual feedback processing within goal-achieved-outcomes is reflected in RP. The location of the ball's impact on the target disk served as graded performance feedback. As in unsuccessful trials the target disk is not hit at all, only more or less successful trials - with positive valence - were analyzed. RP amplitude served as dependent variable. As they influence outcome prediction, we analyzed the effect of hit frequency and preceding trial outcome in each trial. This way, we indirectly took unsuccessful trials into account by investigating their influence on current correct trials. As feedback accuracy and preceding performance vary trial-by-trial, we used linear mixed models that allow for trial-based analysis of covariates and relevant factors. As expected, RP amplitudes gradually increased with increasing accuracy. These effects dovetail with the results reported by Luft et al. (2014) who had found that larger errors produced more negative reward positivity amplitudes. Moreover, our findings mirror reward magnitude effects on RP in correct trials reported in the reward-learning domain (Kreussel et al., 2012; San Martin et al., 2010). Thus, we transfer previous findings on reward magnitude to graded feedback in skill acquisition. Unexpectedly, accuracy feedback interacted with hit frequency.

Whereas the most accurate feedback consistently produced the largest RP, the differentiation between medium and low accuracy feedback vanished, when hit frequency was high. Possibly, this effect is related to effects of adaptive goal setting once a certain level of performance is reached. Similar effects of graded performance feedback on goal setting have been reported previously (Locke, 1968). As to the overall effect of previous performance, RP was globally reduced when hit frequency increased. When hit frequency is high, a positive feedback is rather expected, thus once it is provided the prediction error is small. Hit frequency interacted with training group, with a stronger effect in the high CI group. As in this group all conditions contributed to hit frequency throughout the whole training, it is a better predictor of performance than in the low CI group. Here, performance in the first five blocks was less predictive for performance following the change in target position. This might explain the difference in the frequency effect between groups. RP was locally enhanced for hits after unsuccessful trials. The same reasoning, as for hit frequency, holds for the preceding trial performance effect. After unsuccessful trials, the expectation is adapted towards lower achievement, as would be predicted by temporal difference learning (Sutton & Barto, 1998). Thus, compared to this lower expectation, the positive feedback produces a larger positive prediction error. Hit frequency and preceding trial performance showed the effects expected in the framework of reinforcement learning and proved to be important control variables when examining magnitude effects on RP. Thus we confirm previous assertions on the necessity to control for these variables (Holroyd, 2004; Holroyd et al., 2008). Preceding trial performance had a larger effect when hit frequency was high. In terms of reinforcement predictions, this effect can be interpreted as an online adaptation of expectations as in temporal difference learning. In two separate experiments, between-subjects, reward positivity has been shown to depend on context (Holroyd, Larsen, et al., 2004). Thus, the response to an outcome in reward positivity amplitude does not reflect its (global) absolute magnitude, but this evaluation is flexible and dependent on (local) contextual factors.

Consistent with fMRI findings by Nieuwenhuis et al. (2005), our results suggest influences of both, global and local outcome alternatives and a fast trial-by-trial adaptation of expectations.

In summary, the present study applied predictions from reinforcement learning theory and its neural application to performance monitoring in complex motor skill acquisition. It confirmed and extends previous findings on reward magnitude effects in the reward positivity of correct trials. As we observed graded effects on reward positivity for hits with different degrees of accuracy it complements previous findings on graded feedback effects. In addition, we showed local and global preceding performance effects on reward positivity that can be interpreted as reflecting trial-by-trial adaptations of outcome expectancies.

3. General discussion and future directions

The present dissertation tries to answer the call for the analyses of motor learning in complex tasks (Wulf & Shea, 2002). It is devoted to the CI effect and two stages in the process of motor learning and control: motor preparation and feedback processing. Participants learned to throw at virtual targets either under high or low CI and were subsequently retested for retention and transfer performance. EEG was recorded in both sessions, allowing for an investigation of the underlying neural mechanisms of motor preparation and feedback processing. Moreover, we tested Participants' reasoning ability to shed light on the assumption of individual ability posing a limit on CI effects.

From the results, I conclude, that CI modulates how variability of practice is used for schema formation during parameter learning. I will discuss this interpretation in Section 3.1. Moreover, the abstraction of parameter rules seems to put additional load on the cognitive system. In Section 3.2 I will discuss this hypothesis and integrate it with the theory of two motor processors and the CLT. Finally, I will discuss the locus of the CI effect in motor learning and open questions in Section 3.3.

3.1. Schema formation, CI and variability of practice in parameter learning

Schmidt's Schema theory states that variability of practice enhances experience on the relationship between parameters of a task and outcomes and thereby supports schema formation (Schmidt, 1975). As during schema formation, underlying parameter-outcome rules need to be abstracted, individuals with higher ability in rule abstraction or reasoning (Heit, 2000) should learn faster and better. Schmidt does not make any assumption on spacing between experiences of variants of a task and does hence not explain CI effects. By the end of training the amount of variability of practice is the same under high and low CI and accordingly there should be no difference in retention and transfer (Merbah & Meulemans, 2011; Newell, 2003; C. H. Shea & Wulf, 2005). This interpretation neglects the underlying

mechanism of rule abstraction. Therefore, the distribution of variability of practice and its local impact on schema formation need to be taken into account.

I propose that variability of practice or its absence affects every given trial within the learning history. If under low CI, variability of practice kicks in only after a considerable portion of training, namely when the condition changes for the first time, it cannot previously shape learning in a favorable way. Consistent with this assumption, Study 1 showed that individuals with higher reasoning ability perform significantly better than those with lower reasoning ability, but only under high CI training. Under low CI training, reasoning ability did not relate to performance, neither in training, nor retention or transfer. Only in the final phase of training, after the introduction of the last condition, acquisition curves were steeper for high-reasoning participants. We argue, that schema formation can only be supported by variability of practice, if individuals have sufficient capacity to draw conclusions from varying input. The results of Study 1 support this interpretation and the pattern of results on the relationship of performance improvement with reasoning ability further suggests, that variability of practice is a necessary prerequisite for rule abstraction.

To conclude that the elaboration hypothesis (J. B. Shea & Morgan, 1979) should be favored over the reconstruction hypothesis (Lee & Magill, 1983) is close at hand. Only the elaboration hypothesis explicitly assumes comparison between variants of a task in working memory. Still, prior experience with different task variants might as well alter the motor solution process being reconstructed in a given trial, according to the reconstruction hypothesis. Although given our data the elaboration hypothesis appears more plausible, I cannot safely conclude whether multiple parameter settings are co-activated in working memory or whether they are frequently updated with learning experiences shaping the reconstruction process.

Henceforth, the effect of reasoning ability on motor learning might be two fold: first, directly on the level of problem solving and rule abstraction and second, indirectly mediated

by working memory capacity that limits the amount of information available for the rule abstraction process. These alternatives are hard to differentiate, as working memory and reasoning are highly correlated (Buehner et al., 2005; Kyllonen & Christal, 1990; Süß et al., 2002). Sufficient working memory capacity is a necessary prerequisite for rule abstraction to take place, both as relevant items need to be activated and second, as comparison of these items is a working memory process, too. Reasoning ability covers both processes and should therefore be considered as an estimate of cognitive processing capacity. The effect of CI on cognitive load will be discussed in the next section.

3.2. CI, cognitive load and the two processors in motor learning

Results on the CI effect in complex tasks are heterogeneous (de Croock et al., 1998; Fegghi et al., 2011; Stambaugh, 2011). It is not surprising that despite taking precautions to facilitate CI effects in our investigation, such as a large number of training trials, a parameter manipulation and a pre-learned motor program, we did not yield typical overt CI effects in our performance data. Throwing is a complex task with numerous degrees of freedom and our implementation of this task required the additional coordination of the remote controller that behaved differently from typical projectiles. As a result, even after significant increase with learning, average performance by the end of was below 60% hits. In terms of CLT, inter-element interactions of sub-movements supposedly created a high intrinsic load that prevented the effects of schema formation to reveal in overt behavior (Paas et al., 2003; Sweller, 1988, 1994).

In line with this reasoning, the inconsistency of results on the CI effect in complex tasks was often explained by increased processing demands under high CI that add up with task intrinsic demands and possibly overload processing capacity (Barreiros et al., 2007; Wulf & Shea, 2002; Young et al., 1993). This assumption is supported by fMRI findings, revealing stronger activation of the fronto-parietal attention network under high compared to low CI (Cross et al., 2007). Consistently, the results of Study 1 indicate covert effects of CI and

stronger involvement of cognitive processes in parameter learning under high CI (see Section 3.1). Study 2 provides further evidence on higher cognitive demands under high CI training with stronger reductions in attention and control related components in the ERP in retention. This effect is consistent with a reduction in load with learning, as well as additional effort during schema formation, as assumed by CLT (Paas et al., 2003; Sweller, 1988). Learning related load reduction probably also underlies the smaller activity of the fronto-parietal attention network for successful as compared to unsuccessful trials. Notably this effect was only found for high CI.

Together these results point towards different learning mechanisms under high and low CI. As argued in Section 3.1 rule abstraction requires variability of practice. Thus across large parts of low CI training, rule-based learning cannot take place. Instead the motor system needs to rely on pattern-based learning, which in Study 1 led to massive decline in performance once the condition changed. The differential activation of attention and control related areas could reflect this difference in learning mechanisms. Still, rule-based and pattern-based learning mechanisms are not mutually exclusive, but usually work in parallel when feedback is given (Opitz & Hofmann, 2015). This interpretation is consistent with the notion of two processors (cognitive and motor) in motor learning, as proposed by Verwey (2001) in the sequence learning domain. As the cognitive processor is capacity limited, participants with higher reasoning ability show superior performance (Study 1).

I conclude that in motor learning a cognitive and a motor processor work in parallel. The cognitive processor is more active under high CI learning or given high variability of practice. Here, CI increases cognitive load during motor learning by promoting inter-variant comparison and rule abstraction. These processes are capacity limited and intrinsic load of complex tasks and individual processing capacity mutually determine the amount of capacity available rule abstraction.

3.3. ERP correlates of motor learning and the locus of the CI effect

The present work investigated two stages in motor learning: feedback processing and motor preparation. Feedback provides information on action outcomes and subserves behavioral adaptation according to reinforcement learning theory (Sutton & Barto, 1998). RP, as reflecting prediction error should not only be sensitive to variations in the magnitude of negative, but also positive feedback. In Study 3 we showed such effects of graded positive performance feedback on RP amplitude. These results complement earlier findings on graded error feedback being reflected in RP with larger negativities for larger errors (Luft et al., 2014). As predicted by reinforcement theory measures of expectancy, such as hit frequency and successful preceding trial performance produced smaller RP amplitudes. This effect supports the interpretation of RP reflecting signed prediction error and underlines the importance of controlling for expectancy measures when investigating magnitude effects on RP (Holroyd, 2004; Holroyd & Coles, 2002; Holroyd et al., 2008). Further, our results indicated that outcome predictions are flexibly adapted trial by trial, as for example negative preceding performance had a larger impact in trials when hit frequency was high. High performance moreover seems to lead to a dedifferentiation between medium and low accuracy performance feedback. This result is consistent with adaptive goal setting found for graded performance feedback (Locke, 1968). It is yet unclear how precisely feedback information is translated changes in motor behavior. Whereas simple reinforcement mechanisms might strengthen the representations of successful movements, additional processes must recalibrate parameter settings after errors. This gap remains to be bridged.

Motor learning goes along with a fronto-parietal shift, as reflected in a decrease in P3 and an increase in motor preparatory activity (Staines et al., 2002). Whereas in Study 2 the reduction in the cue related P3 was not affected by training schedule, motor preparatory activity was. The increase in ICNV from training to retention in the low CI group replicates previous findings. In contrast, there was a significant decrease in iCNV and a trend for a

decrease in ICNV from training to retention in the high CI group. We concluded that CI effects might cover the effects on the frontal-parietal shift associated with motor learning in the motor component by increasing activation of the cognitive processor during training. In Study 2, we propose, that activity of both processors is reflected in CNV amplitude.

Contributions of the frontal-parietal attention network to CNV have been reported previously using source localization (Gomez, Flores, & Ledesma, 2007). The findings were interpreted as endogenous attentional efforts to support motor preparation. Differential activation of cognitive and motor processor by high and low CI might explain contradictory effects of learning on ICNV.

Concerning the locus of the CI effect, we found strong evidence, that high CI does indeed produce higher demands on cognitive processing during the preparatory stage. The feedback accuracy effect did not interact with CI. Only control variables, such as hit frequency and target position interacted with CI. These effects are supposedly related to differences in performance and its distribution across training, but do not allow for the assumption of differential processing between CI groups. Whereas “absence of evidence is not evidence of absence” (Altman & Bland, 1995), together with the results from Study 2 and previous literature (Cross et al., 2007), motor preparation, rather than feedback processing is affected by CI. Possibly, processes translating feedback information to motor preparation, such as adaptation processes or updating of the motor schema might be the original source of the differences. In the simplified process model of motor learning presented in section 1.2 the latter process would relate to the “Get information” stage. Notably, P3 amplitude did neither differ between groups, nor did CI significantly affect its learning related decrease. The amplification of control and attention related activity during the preparatory stage rather indicates higher cognitive processes modulating motor preparation.

3.4. Conclusions

Integrating the results from Study 1, 2 and 3, I conclude that, informed by feedback processing, cognitive and motor processes run in parallel during motor learning. Both processors contribute to ICNV amplitude. The contribution of cognitive processes is higher under high CI during learning. This is further supported by the enhanced activation of the fronto-parietal attention network. Given variability of practice and sufficient cognitive capacity, Individuals abstract rules to schemata that allow for flexible transfer in parameter adaptation. This interpretation is consistent with the elaboration hypothesis (J. B. Shea & Morgan, 1979). Feedback about the outcome is a prerequisite for rule-based learning (Opitz & Hofmann, 2015) and of special importance for the acquisition of complex tasks (Wulf & Shea, 2002). Graded positive performance feedback modulates RP amplitude and effects of expectancy measures indicate a fast trial-by trial adaptation of expectations and hint towards adaptive goal setting with increasing performance. A question remaining for future research is how feedback information translates to parameter adaptation and which brain processes reflect this translation.

References

- Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology: General*, *117*(3), 288-318. doi:10.1037/0096-3445.117.3.288
- Ackerman, P. L., & Cianciolo, A. T. (2000). Cognitive, perceptual-speed, and psychomotor determinants of individual differences during skill acquisition. *J Exp Psychol Appl*, *6*(4), 259-290. doi:10.1037/1076-898X.6.4.259
- Albaret, J. M., & Thon, B. (1998). Differential effects of task complexity on contextual interference in a drawing task. *Acta Psychol (Amst)*, *100*(1-2), 9-24. doi:10.1016/s0001-6918(98)00022-5
- Altman, D. G., & Bland, J. M. (1995). Absence of evidence is not evidence of absence. *British Medical Journal*, *311*, 485. doi:10.1136/bmj.311.7003.485
- Anguera, J. A., Seidler, R. D., & Gehring, W. J. (2009). Changes in performance monitoring during sensorimotor adaptation. *J Neurophysiol*, *102*(3), 1868-1879. doi:10.1152/jn.00063.2009
- Arbel, Y., Goforth, K., & Donchin, E. (2013). The good, the bad, or the useful? The examination of the relationship between the feedback-related negativity (FRN) and long-term learning outcomes. *J Cogn Neurosci*, *25*(8), 1249-1260. doi:10.1162/jocn_a_00385
- Arbel, Y., Murphy, A., & Donchin, E. (2014). On the utility of positive and negative feedback in a paired-associate learning task. *J Cogn Neurosci*, *26*(7), 1445-1453. doi:10.1162/jocn_a_00617
- Baker, T. E., & Holroyd, C. B. (2011). Dissociated roles of the anterior cingulate cortex in reward and conflict processing as revealed by the feedback error-related negativity and N200. *Biol Psychol*, *87*(1), 25-34. doi:10.1016/j.biopsycho.2011.01.010

- Band, G. P., van Steenbergen, H., Ridderinkhof, K. R., Falkenstein, M., & Hommel, B. (2009). Action-effect negativity: irrelevant action effects are monitored like relevant feedback. *Biol Psychol*, *82*(3), 211-218. doi:10.1016/j.biopsycho.2009.06.011
- Barreiros, J., Figueiredo, T., & Godinho, M. (2007). The contextual interference effect in applied settings. *European Physical Education Review*, *13*(2), 195-208. doi:10.1177/1356336x07076876
- Beaunieux, H., Hubert, V., Witkowski, T., Pitel, A. L., Rossi, S., Danion, J. M., . . . Eustache, F. (2006). Which processes are involved in cognitive procedural learning? *Memory*, *14*(5), 521-539. doi:10.1080/09658210500477766
- Becker, M. P., Nitsch, A. M., Miltner, W. H., & Straube, T. (2014). A single-trial estimation of the feedback-related negativity and its relation to BOLD responses in a time-estimation task. *J Neurosci*, *34*(8), 3005-3012. doi:10.1523/JNEUROSCI.3684-13.2014
- Bellebaum, C., & Colosio, M. (2014). From feedback- to response-based performance monitoring in active and observational learning. *J Cogn Neurosci*, *26*(9), 2111-2127. doi:10.1162/jocn_a_00612
- Bender, S., Resch, F., Weisbrod, M., & Oelkers-Ax, R. (2004). Specific task anticipation versus unspecific orienting reaction during early contingent negative variation. *Clin Neurophysiol*, *115*(8), 1836-1845. doi:10.1016/j.clinph.2004.03.023
- Brady, F. (2004). Contextual interference: a meta-analytic study. *Percept Mot Skills*, *99*(1), 116-126. doi:10.2466/pms.99.1.116-126
- Brunia, C. H. (2004). Slow potentials in anticipatory behavior. *Journal of Psychophysiology*, *18*(2-3), 59-60. doi:10.1027/0269-8803.18.2-3.59
- Brunia, C. H., & Damen, E. J. (1988). Distribution of slow brain potentials related to motor preparation and stimulus anticipation in a time estimation task. *Electroencephalogr Clin Neurophysiol*, *69*(3), 234-243. doi:10.1016/0013-4694(88)90132-0

- Buehner, M., Krumm, S., & Pick, M. (2005). Reasoning=working memory≠attention. *Intelligence*, 33(3), 251-272. doi:10.1016/j.intell.2005.01.002
- Cavanagh, J. F., Frank, M. J., Klein, T. J., & Allen, J. J. (2010). Frontal theta links prediction errors to behavioral adaptation in reinforcement learning. *NeuroImage*, 49(4), 3198-3209. doi:10.1016/j.neuroimage.2009.11.080
- Chiviawowsky, S., & Wulf, G. (2007). Feedback after good trials enhances learning. *Res Q Exerc Sport*, 78(2), 40-47. doi:10.1080/02701367.2007.10599402
- Cohen, M. X., Elger, C. E., & Ranganath, C. (2007). Reward expectation modulates feedback-related negativity and EEG spectra. *NeuroImage*, 35(2), 968-978. doi:10.1016/j.neuroimage.2006.11.056
- Cross, E. S., Schmitt, P. J., & Grafton, S. T. (2007). Neural substrates of contextual interference during motor learning support a model of active preparation. *J Cogn Neurosci*, 19(11), 1854-1871. doi:10.1162/jocn.2007.19.11.1854
- de Croock, M. B. M., van Merriënboer, J. J. G., & Paas, F. G. W. C. (1998). High versus low contextual interference in simulation-based training of troubleshooting skills: effects on transfer performance and invested mental effort. *Computers in Human Behavior*, 14(2), 249-267. doi:10.1016/s0747-5632(98)00005-3
- De Kleine, E., & Van der Lubbe, R. H. (2011). Decreased load on general motor preparation and visual-working memory while preparing familiar as compared to unfamiliar movement sequences. *Brain Cogn*, 75(2), 126-134. doi:10.1016/j.bandc.2010.10.013
- Eppinger, B., Kray, J., Mock, B., & Mecklinger, A. (2008). Better or worse than expected? Aging, learning, and the ERN. *Neuropsychologia*, 46(2), 521-539. doi:10.1016/j.neuropsychologia.2007.09.001
- Farrow, D., & Maschette, W. (1997). The effects of contextual interference on children learning forehand tennis groundstrokes. *Journal of Human Movement Studies*, 33(2), 47-67. Retrieved from <Go to ISI>://WOS:000072677900001

- Fegghi, I., Abdoli, B., & Valizadeh, R. (2011). Compare contextual interference effect and practice specificity in learning basketball free throw. *Procedia - Social and Behavioral Sciences, 15*(0), 2176-2180. doi:10.1016/j.sbspro.2011.04.075
- Frömer, R., Hafner, V., & Sommer, W. (2012). Aiming for the bull's eye: Preparing for throwing investigated with event-related brain potentials. *Psychophysiology, 49*(3), 335-344. doi:10.1111/j.1469-8986.2011.01317.x
- Gomez, C. M., Flores, A., & Ledesma, A. (2007). Fronto-parietal networks activation during the contingent negative variation period. *Brain Res Bull, 73*(1-3), 40-47. doi:10.1016/j.brainresbull.2007.01.015
- Guadagnoli, M. A., Holcomb, W. R., & Weber, T. J. (1999). The relationship between contextual interference effects and performer expertise on the learning of a putting task. *Journal of Human Movement Studies, 37*(1), 19-36. Retrieved from <Go to ISI>://WOS:000081548600002
- Hajcak, G., Holroyd, C. B., Moser, J. S., & Simons, R. F. (2005). Brain potentials associated with expected and unexpected good and bad outcomes. *Psychophysiology, 42*(2), 161-170. doi:10.1111/j.1469-8986.2005.00278.x
- Hajcak, G., Moser, J. S., Holroyd, C. B., & Simons, R. F. (2006). The feedback-related negativity reflects the binary evaluation of good versus bad outcomes. *Biol Psychol, 71*(2), 148-154. doi:10.1016/j.biopsycho.2005.04.001
- Hall, K. G., Domingues, D. A., & Cavazos, R. (1994). Contextual interference effects with skilled baseball players. *Percept Mot Skills, 78*(3 Pt 1), 835-841. doi:10.2466/pms.1994.78.3.835
- Hebert, E. P., Landin, D., & Solmon, M. A. (1996). Practice schedule effects on the performance and learning of low- and high-skilled students: an applied study. *Res Q Exerc Sport, 67*(1), 52-58. doi:10.1080/02701367.1996.10607925

- Heit, E. (2000). Properties of inductive reasoning. *Psychon Bull Rev*, 7(4), 569-592.
doi:10.3758/BF03212996
- Henderson, S. E. (1977). Role of feedback in the development and maintenance of complex skill. *J Exp Psychol Hum Percept Perform*, 3(2), 224-233. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/864394>
- Holroyd, C. B. (2004). A note on the oddball N200 and the feedback ERN. In M. Ullsperger & M. Falkenstein (Eds.), *Errors, Conflicts, and the Brain. Current Opinions on Performance Monitoring* (pp. 211–218). Leipzig: MPI of Cognitive Neuroscience.
- Holroyd, C. B., & Coles, M. G. (2002). The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychol Rev*, 109(4), 679-709. doi:10.1037/0033-295X.109.4.679
- Holroyd, C. B., Hajcak, G., & Larsen, J. T. (2006). The good, the bad and the neutral: electrophysiological responses to feedback stimuli. *Brain Res*, 1105(1), 93-101.
doi:10.1016/j.brainres.2005.12.015
- Holroyd, C. B., Krigolson, O. E., & Lee, S. (2011). Reward positivity elicited by predictive cues. *Neuroreport*, 22(5), 249-252. doi:10.1097/WNR.0b013e328345441d
- Holroyd, C. B., Larsen, J. T., & Cohen, J. D. (2004). Context dependence of the event-related brain potential associated with reward and punishment. *Psychophysiology*, 41(2), 245-253. doi:10.1111/j.1469-8986.2004.00152.x
- Holroyd, C. B., Nieuwenhuis, S., Yeung, N., & Cohen, J. D. (2003). Errors in reward prediction are reflected in the event-related brain potential. *Neuroreport*, 14(18), 2481-2484. doi:10.1097/01.wnr.0000099601.41403.a5
- Holroyd, C. B., Nieuwenhuis, S., Yeung, N., Nystrom, L., Mars, R. B., Coles, M. G., & Cohen, J. D. (2004). Dorsal anterior cingulate cortex shows fMRI response to internal and external error signals. *Nat Neurosci*, 7(5), 497-498. doi:10.1038/nn1238

- Holroyd, C. B., Pakzad-Vaezi, K. L., & Krigolson, O. E. (2008). The feedback correct-related positivity: sensitivity of the event-related brain potential to unexpected positive feedback. *Psychophysiology*, *45*(5), 688-697. doi:10.1111/j.1469-8986.2008.00668.x
- Jansma, J. M., Ramsey, N. F., Slagter, H. A., & Kahn, R. S. (2001). Functional anatomical correlates of controlled and automatic processing. *J Cogn Neurosci*, *13*(6), 730-743. doi:10.1162/08989290152541403
- Kreussel, L., Hewig, J., Kretschmer, N., Hecht, H., Coles, M. G., & Miltner, W. H. (2012). The influence of the magnitude, probability, and valence of potential wins and losses on the amplitude of the feedback negativity. *Psychophysiology*, *49*(2), 207-219. doi:10.1111/j.1469-8986.2011.01291.x
- Kujawa, A., Smith, E., Luhmann, C., & Hajcak, G. (2013). The feedback negativity reflects favorable compared to nonfavorable outcomes based on global, not local, alternatives. *Psychophysiology*, *50*(2), 134-138. doi:10.1111/psyp.12002
- Kyllonen, P. C., & Christal, R. E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence*, *14*(4), 389-433. doi:10.1016/s0160-2896(05)80012-1
- Lee, T. D., & Magill, R. A. (1983). The Locus of Contextual Interference in Motor-Skill Acquisition. *Journal of Experimental Psychology-Learning Memory and Cognition*, *9*(4), 730-746. doi:10.1037//0278-7393.9.4.730
- Leuthold, H., & Jentzsch, I. (2001). Neural correlates of advance movement preparation: a dipole source analysis approach. *Brain Res Cogn Brain Res*, *12*(2), 207-224. doi:10.1016/S0926-6410(01)00052-0
- Leuthold, H., Sommer, W., & Ulrich, R. (2004). Preparing for action: Inferences from CNV and LRP. *Journal of Psychophysiology*, *18*(2-3), 77-88. doi:10.1027/0269-880318.2-3.77

- Locke, E. A. (1968). Effects of knowledge of results, feedback in relation to standards, and goals on reaction-time performance. *Am J Psychol*, *81*(4), 566-574.
doi:10.2307/1421061
- Luft, C. D., Takase, E., & Bhattacharya, J. (2014). Processing graded feedback: electrophysiological correlates of learning from small and large errors. *J Cogn Neurosci*, *26*(5), 1180-1193. doi:10.1162/jocn_a_00543
- Lukie, C. N., Montazer-Hojat, S., & Holroyd, C. B. (2014). Developmental changes in the reward positivity: an electrophysiological trajectory of reward processing. *Dev Cogn Neurosci*, *9*, 191-199. doi:10.1016/j.dcn.2014.04.003
- Merbah, S., & Meulemans, T. (2011). Learning a Motor Skill: Effects of Blocked Versus Random Practice a Review. *Psychologica Belgica*, *51*(1), 15-48. doi:10.5334/pb-51-1-15
- Miltner, W. H., Braun, C. H., & Coles, M. G. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: evidence for a "generic" neural system for error detection. *J Cogn Neurosci*, *9*(6), 788-798. doi:10.1162/jocn.1997.9.6.788
- Müller-Gethmann, H., Ulrich, R., & Rinkenauer, G. (2003). Locus of the effect of temporal preparation: evidence from the lateralized readiness potential. *Psychophysiology*, *40*(4), 597-611. doi:10.1111/1469-8986.00061
- Newell, K. M. (2003). Schema theory (1975): retrospectives and prospectives. *Res Q Exerc Sport*, *74*(4), 383-388. doi:10.1080/02701367.2003.10609108
- Nieuwenhuis, S., Heslenfeld, D. J., von Geusau, N. J. A., Mars, R. B., Holroyd, C. B., & Yeung, N. (2005). Activity in human reward-sensitive brain areas is strongly context dependent. *NeuroImage*, *25*(4), 1302-1309. doi:10.1016/j.neuroimage.2004.12.043
- Nieuwenhuis, S., Yeung, N., Holroyd, C. B., Schurger, A., & Cohen, J. D. (2004). Sensitivity of electrophysiological activity from medial frontal cortex to utilitarian and performance feedback. *Cereb Cortex*, *14*(7), 741-747. doi:10.1093/cercor/bhh034

- Opitz, B., & Friederici, A. D. (2003). Interactions of the hippocampal system and the prefrontal cortex in learning language-like rules. *NeuroImage*, *19*(4), 1730-1737. doi:10.1016/S1053-8119(03)00170-8
- Opitz, B., & Hofmann, J. (2015). Concurrence of rule- and similarity-based mechanisms in artificial grammar learning. *Cogn Psychol*, *77*, 77-99. doi:10.1016/j.cogpsych.2015.02.003
- Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38*(1), 1-4. doi:10.1207/S15326985ep3801_1
- Pinto Zipp, G., & Gentile, A. (2010). Practice schedule and the learning of motor skills in children and adults: teaching implications. *Journal of College Teaching & Learning (TLC)*, *7*(2).
- Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clin Neurophysiol*, *118*(10), 2128-2148. doi:10.1016/j.clinph.2007.04.019
- Potts, G. F., Martin, L. E., Burton, P., & Montague, P. R. (2006). When things are better or worse than expected: the medial frontal cortex and the allocation of processing resources. *J Cogn Neurosci*, *18*(7), 1112-1119. doi:10.1162/jocn.2006.18.7.1112
- Potts, G. F., Martin, L. E., Kamp, S. M., & Donchin, E. (2011). Neural response to action and reward prediction errors: Comparing the error-related negativity to behavioral errors and the feedback-related negativity to reward prediction violations. *Psychophysiology*, *48*(2), 218-228. doi:10.1111/j.1469-8986.2010.01049.x
- Prescott, J. (1986). The effects of response parameters on CNV amplitude. *Biol Psychol*, *22*(2), 107-135. doi:10.1016/0301-0511(86)90039-6
- Rose, M., Verleger, R., & Wascher, E. (2001). ERP correlates of associative learning. *Psychophysiology*, *38*(3), 440-450. doi:10.1111/1469-8986.3830440

- Ruchkin, D. S., Canoune, H. L., Johnson, R., Jr., & Ritter, W. (1995). Working memory and preparation elicit different patterns of slow wave event-related brain potentials. *Psychophysiology*, 32(4), 399-410. doi:10.1111/j.1469-8986.1995.tb01223.x
- Sakai, K., Hikosaka, O., Miyauchi, S., Takino, R., Sasaki, Y., & Putz, B. (1998). Transition of brain activation from frontal to parietal areas in visuomotor sequence learning. *J Neurosci*, 18(5), 1827-1840. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/9465007>
- Sakai, K., Ramnani, N., & Passingham, R. E. (2002). Learning of sequences of finger movements and timing: frontal lobe and action-oriented representation. *J Neurophysiol*, 88(4), 2035-2046. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/12364526>
- Salmoni, A. W., Schmidt, R. A., & Walter, C. B. (1984). Knowledge of results and motor learning: a review and critical reappraisal. *Psychol Bull*, 95(3), 355-386. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/6399752>
- Sambrook, T. D., & Goslin, J. (2015). A neural reward prediction error revealed by a meta-analysis of ERPs using great grand averages. *Psychol Bull*, 141(1), 213-235. doi:10.1037/bul0000006
- San Martin, R., Manes, F., Hurtado, E., Isla, P., & Ibanez, A. (2010). Size and probability of rewards modulate the feedback error-related negativity associated with wins but not losses in a monetarily rewarded gambling task. *NeuroImage*, 51(3), 1194-1204. doi:10.1016/j.neuroimage.2010.03.031
- Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, 82(4), 225-260. doi:10.1037/h0076770
- Segalowitz, S. J., Wintink, A. J., & Cudmore, L. J. (2001). P3 topographical change with task familiarization and task complexity. *Brain Res Cogn Brain Res*, 12(3), 451-457. doi:10.1016/S0926-6410(01)00082-9

- Shadmehr, R., & Holcomb, H. H. (1997). Neural correlates of motor memory consolidation. *Science*, 277(5327), 821-825. doi:10.1126/science.277.5327.821
- Shea, C. H., Kohl, R., & Indermill, C. (1990). Contextual Interference - Contributions of Practice. *Acta Psychologica*, 73(2), 145-157. doi:10.1016/0001-6918(90)90076-R
- Shea, C. H., & Wulf, G. (2005). Schema theory: a critical appraisal and reevaluation. *J Mot Behav*, 37(2), 85-101. doi:10.3200/JMBR.37.2.85-102
- Shea, J. B., & Morgan, R. L. (1979). Contextual interference effects on the acquisition, retention, and transfer of a motor skill. *Journal of Experimental Psychology: Human Learning & Memory*, 5(2), 179-187. doi:10.1037/0278-7393.5.2.179
- Staines, W. R., Padilla, M., & Knight, R. T. (2002). Frontal-parietal event-related potential changes associated with practising a novel visuomotor task. *Brain Res Cogn Brain Res*, 13(2), 195-202. doi:10.1016/S0926-6410(01)00113-6
- Stambaugh, L. A. (2011). When Repetition Isn't the Best Practice Strategy: Effects of Blocked and Random Practice Schedules. *Journal of Research in Music Education*, 58(4), 368-383. doi:10.1177/0022429410385945
- Süß, H.-M., Oberauer, K., Wittmann, W. W., Wilhelm, O., & Schulze, R. (2002). Working-memory capacity explains reasoning ability - and a little bit more. *Intelligence*, 30(3), 261-288. doi:10.1016/S0160-2896(01)00100-3
- Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction*. Cambridge: MIT press.
- Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257-285. doi:10.1016/0364-0213(88)90023-7
- Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction*, 4(4), 295-312. doi:10.1016/0959-4752(94)90003-5

- Toni, I., Krams, M., Turner, R., & Passingham, R. E. (1998). The time course of changes during motor sequence learning: a whole-brain fMRI study. *NeuroImage*, *8*(1), 50-61. doi:10.1006/nimg.1998.0349
- Ulrich, N., & Hewig, J. (2014). A miss is as good as a mile? Processing of near and full outcomes in a gambling paradigm. *Psychophysiology*, *51*(9), 819-823. doi:10.1111/psyp.12232
- van Boxtel, G. J., & Brunia, C. H. (1994). Motor and non-motor aspects of slow brain potentials. *Biol Psychol*, *38*(1), 37-51. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/7999929>
- Van Boxtel, G. J., Van den Boogaart, B., & Brunia, C. H. (1993). The contingent negative variation in a choice reaction time task. *Journal of Psychophysiology*.
- Van Der Helden, J., & Boksem, M. A. (2012). Medial frontal negativity reflects learning from positive feedback. *Psychophysiology*, *49*(8), 1109-1113. doi:10.1111/j.1469-8986.2012.01388.x
- Verleger, R., Wauschkuhn, B., van der Lubbe, R., Jaskowski, P., & Trillenberg, P. (2000). Posterior and anterior contribution of hand-movement preparation to late CNV. *Journal of Psychophysiology*, *14*(2), 69-86. doi:10.1027//0269-8803.14.2.69
- Verwey, W. B. (2001). Concatenating familiar movement sequences: the versatile cognitive processor. *Acta Psychol (Amst)*, *106*(1-2), 69-95. doi:10.1016/S0001-6918(00)00027-5
- Walsh, M. M., & Anderson, J. R. (2012). Learning from experience: event-related potential correlates of reward processing, neural adaptation, and behavioral choice. *Neurosci Biobehav Rev*, *36*(8), 1870-1884. doi:10.1016/j.neubiorev.2012.05.008
- Wascher, E., Verleger, R., Jaskowski, P., & Wauschkuhn, B. (1996). Preparation for action: An ERP study about two tasks provoking variability in response speed. *Psychophysiology*, *33*(3), 262-272. doi:10.1111/J.1469-8986.1996.Tb00423.X

- Wild-Wall, N., Sangals, J., Sommer, W., & Leuthold, H. (2003). Are fingers special? Evidence about movement preparation from event-related brain potentials. *Psychophysiology*, *40*(1), 7-16. doi:10.1111/1469-8986.00002
- Woltz, D. J. (1988). An Investigation of the Role of Working Memory in Procedural Skill Acquisition. *Journal of Experimental Psychology-General*, *117*(3), 319-331. doi:10.1037/0096-3445.117.3.319
- Wulf, G., & Lee, T. D. (1993). Contextual interference in movements of the same class: differential effects on program and parameter learning. *J Mot Behav*, *25*(4), 254-263. doi:10.1080/00222895.1993.9941646
- Wulf, G., Shea, C., & Lewthwaite, R. (2010). Motor skill learning and performance: a review of influential factors. *Med Educ*, *44*(1), 75-84. doi:10.1111/j.1365-2923.2009.03421.x
- Wulf, G., & Shea, C. H. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychon Bull Rev*, *9*(2), 185-211. doi:10.3758/bf03196276
- Young, D. E., Cohen, M. J., & Husak, W. S. (1993). Contextual Interference and Motor Skill Acquisition - on the Processes That Influence Retention. *Human Movement Science*, *12*(5), 577-600. doi:10.1016/0167-9457(93)90005-A

Original Articles

Paper I:

Frömer, R., Stürmer, B., & Sommer, W. (submitted). Come to think of it: Contributions of reasoning abilities and training schedule to skill acquisition in a virtual throwing task.

Manuscript under review for Acta Psychologica

Paper II:

Frömer, R., Stürmer, B., & Sommer, W. (submitted). (Don't) Mind the effort: effects of contextual interference on ERP indicators of motor preparation. *Manuscript under review for Psychophysiology*

Paper III:

Frömer, R., Stürmer, B., & Sommer, W. (2016). The better, the bigger: The effect of graded positive performance feedback on the reward positivity. *Biol Psychol*, *114*, 61-68.

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