Received: 18 August 2022 | Revised: 18 August 2023 | Accepted: 23 August 2023

DOI: 10.1111/psyp.14439

PSYCHOPHYSIOLOGY SPR WILEY

REVIEW

Feedback processing in cognitive and motor tasks: A meta-analysis on the feedback-related negativity

Laura Faßbender[1] | **Daniel Krause**[2] | **Matthias Weigelt**[2]

[1]Department of Psychology, Justus-Liebig-University Gießen, Gießen, Germany

[2]Department of Exercise and Health, Paderborn University, Paderborn, Germany

Correspondence
Laura Faßbender, Developmental Psychology, Department of Psychology, Faculty of Psychology and Sport Science, Justus-Liebig-University Gießen, Otto-Behaghel-Str. 10F, Gießen 35394, Germany.
Email: laura.fassbender@psychol.uni-giessen.de

Funding information
Cluster Initiative The Adaptive Mind by the Hessian Ministry of Higher Education, Research, Science and the Arts

[Correction added on October 18, 2023 after first online publication: The y axis in Figure 8 has been modified.]

Abstract

For motor learning, the processing of behavioral outcomes is of high significance. The feedback-related negativity (FRN) is an event-related potential, which is often described as a correlate of the reward prediction error in reinforcement learning. The number of studies examining the FRN in motor tasks is increasing. This meta-analysis summarizes the component in the motor domain and compares it to the cognitive domain. Therefore, a data set of a previous meta-analysis in the cognitive domain that comprised 47 studies was reanalyzed and compared to additional 25 studies of the motor domain. Further, a moderator analysis for the studies in the motor domain was conducted. The FRN amplitude was higher in the motor domain than in the cognitive domain. This might be related to a higher task complexity and a higher feedback ambiguity of motor tasks. The FRN latency was shorter in the motor domain than in the cognitive domain. Given that sensory information can be used as an external feedback predictor prior to the presentation of the final feedback, reward processing in the motor domain may have been faster and reduced the FRN latency. The moderator variable analysis revealed that the feedback modality influenced the FRN latency, with shorter FRN latencies after bimodal than after visual feedback. Processing of outcome feedback seems to share basic principles in both domains; however, differences exist and should be considered in FRN studies. Future research is motivated to scrutinize the effects of bimodal feedback and other moderators within the motor domain.

KEYWORDS

ACC, ERPs, error processing, motor learning, reinforcement learning, reward positivity

1 | INTRODUCTION

1.1 | The feedback-related negativity in the motor domain

The processing of outcome information (i.e., external feedback) provided by behavioral effects on the environment (e.g., a ball flight) or by a teaching person (e.g., verbal feedback) is essential for motor learning. It supplements intrinsic (e.g., kinaesthetic) feedback information, which is generally a comparably more ambiguous source of information to evaluate the quality of one's own movement executions (Seidler et al., 2013). Besides that, processing the discrepancy between intrinsic (subjective) and extrinsic (objective) error information (i.e., prediction errors) enhances motor learning (Wolpert & Kawato, 1998). Neural correlates of error processing are reflected in event-related potentials of the electroencephalogram (EEG) signal and help to understand the neuro-cognitive underpinnings of feedback-dependent learning. The feedback-related negativity (FRN), which is also called reward positivity (RewP; Krigolson, 2018), and less often called medial-frontal negativity (MFN; e.g., Mushtaq et al., 2022), is the most prominent component associated to reinforcement learning (Holroyd & Coles, 2002; Miltner et al., 1997; Schultz, 2002). The FRN can be elicited at frontal sites 200–300 ms after feedback onset, being more negative after negative feedback than after positive feedback. The FRN reflects a (signed) reward prediction error (RPE) in reinforcement learning processes, with stronger deflections after unexpected feedback (Holroyd & Coles, 2002; Miltner et al., 1997; San Martín, 2012; Schultz, 2002; Walsh & Anderson, 2012). These are mediated by phasic activity of midbrain dopamine neurons and respective projections to the striatum, as well as the dorsal anterior cingulate cortex (dACC; e.g., Gehring & Willoughby, 2002; Glimcher, 2011), which is a part of the cognitive control network (Chein & Schneider, 2012; Seidler et al., 2013).

It has been shown that different aspects of external feedback presentation influence the FRN amplitude. For instance, not only the valence signal of feedback induces neural correlates in such time frames, but also the value of the prediction error, driven by motivational saliency, and the interaction of both (Kirsch et al., 2022; Sambrook & Goslin, 2015; Stewardson & Sambrook, 2023). Furthermore, a previous meta-analysis pointed out that the FRN can also emerge earlier than original articles postulated, suggesting time ranges of 150–400 ms for valence effects or 240–340 ms for RPE effects (Kirsch et al., 2022; Sambrook & Goslin, 2015).

There is also an ongoing debate about whether the FRN should be interpreted as a negativity or rather a reward positivity (RewP) that can be seen as a P300 leading to a reduced N200 amplitude. Two overviews of this debate were provided by Krigolson (2018) and Proudfit (2015). Both authors demonstrated that the use of differential waveforms allows for a rapid switching between FRN (negative–positive feedback) and RewP (positive–negative feedback), by simply inverting each other, making both definitions interchangeable. However, it is worth noting that the FRN approach focuses more on the error processing of feedback, while the RewP approach addresses the processing of rewards (e.g., Cockburn & Holroyd, 2018; Proudfit, 2015). Within the present paper, the term FRN is used because of the following reasons: The term FRN is still more often used than the term RewP, especially in the motor domain (e.g., Maurer et al., 2021). The differentiation of the FRN in the motor domain is special insofar as it has been described to reflect the postdictive error processing that is associated with the neural response to external feedback after movement execution. This contrasts with the error-related negativity (ERN) that reflects the predictive (internal) error processing before external feedback is present (Holroyd & Coles, 2002; Maurer et al., 2021; Walsh & Anderson, 2012). Error processing contributes significantly to motor learning, since external feedback information (e.g., verbal feedback of coaches, video feedback, biomechanical data, etc.) can be used to support performance evaluation and improvement (Maurer et al., 2021; Nikooyan & Ahmed, 2015). Importantly, the use of difference waves to evaluate the neural signatures of feedback processing within the meta-analysis makes the comparability of both conceptual distinctions possible.

1.2 | Domain-specific differences in feedback processing related to the feedback-related negativity

There is already a large amount of research on the FRN in the cognitive domain (cf., meta-analysis of Sambrook & Goslin, 2015), while the number of publications focusing on the motor domain is substantially smaller but has also increased in recent years (cf., Maurer et al., 2021). Current research starts to investigate how the characteristic of external feedback affects behavior (adaptation and learning), by analyzing neural correlates of feedback processing that are related to different mechanisms (e.g., Arbel et al., 2017; Kirsch et al., 2022). Due to different characteristics, it seems reasonable to differentiate motor tasks and cognitive tasks. Tasks in the cognitive domain comprise decision-making with more (e.g., paired associate learning; Arbel et al., 2013) or less learnable tasks (e.g., gambling; Liu et al., 2017), different stimulus–response–reward mappings, time estimation tasks (e.g., Cockburn & Holroyd, 2018), and other tasks with minimal demands on motor control. In motor tasks, people learn to predict the outcome of an action, especially in later stages of motor learning. Therefore, feedforward models and inverse models are used to plan motor commands and predict action outcomes, while the feedback loop is used to compare desired outcomes and actual outcomes to modify the following movement executions (Künzell, 2023; Winstein et al., 1994). Within this process, it has been shown by a semi-virtual throwing task that the FRN, as a neural correlate for the postdictive error processing of external feedback, can be differentiated from the ERN, as a neural correlate of predictive error processing of internal feedback, since the FRN amplitude usually decreases with learning, while the ERN amplitude increases (Maurer et al., 2022). Another characteristic of motor tasks is that errors can arise in response selection as well as in response execution, whereas errors in cognitive tasks only refer to response selection (Maurer et al., 2021). This can result in a higher complexity and a higher ambiguity of feedback since errors can arise at different time points and for different task elements.

1.3 | Aim of the meta-analysis

The current meta-analysis scrutinizes the FRN amplitude and the FRN latency in the motor domain, first, to compare it to meta-analytic findings in the cognitive domain (cf., Sambrook & Goslin, 2015), and second, to reveal moderating factors within the motor domain. The previous meta-analysis of the FRN in the cognitive domain by Sambrook and Goslin (2015) focused on the influence of reward magnitude and likelihood on the FRN and found strong effects for both the RPE-FRN (difference in the high magnitude/likelihood and low magnitude/likelihood) and the FRN (as a pure valence measure). We categorized those studies into the cognitive domain in which a motor action was required, but where the movement itself was not critical for task performance and (performance) feedback was also not related to movement execution. Mostly, this included studies using simple responses (such as a single key press), for which movement execution relied on well-established, highly automatized motor representations (cf., Fitts & Posner, 1967) that had not been acquired within these studies. Accordingly, task performance in these studies depended on fast and correct decision-making by selecting a previously established motor action (e.g., pressing a certain key) but did not rely on its execution parameters. In contrast, we categorized those studies into the motor domain in which a motor action was required and movement execution determined task performance (and feedback) based on the movement's own and/or outcome-related temporal and/or spatial properties. Thus, task performance depended on the quality and/or quantity of movement execution, rather than on the selection of a particular motor action within a decision-making process.

Although both domains share several principles of information processing, it seems reasonable to ask the question of how feedback processing in the motor domain differs from the cognitive domain for several reasons: (1) Whereas responses in cognitive tasks are usually rather simple (e.g., single button press), responses in motor tasks are typically more complex (i.e., number of successive and simultaneous response elements; e.g., playing a sequence of key presses on a piano with one hand only [successive elements] or with both hands [simultaneous elements]). This leads to a multitude of informational resources based on intrinsic feedback of various perceptual systems; (2) a large *response complexity* (almost inevitably) increases the *assignment ambiguity*, because the execution of multiple elements of a complex motor action, which requires the control of a large number of degrees of freedom (Bernstein, 1967), will induce more errors than the execution of simple responses. This makes it difficult to relate these errors to individual elements of the complex action; (3) motivational saliency might be higher in motor tasks than in cognitive tasks, because feedback has a higher relevance for learning the motor task; and (4) internal information from efference copies and ongoing re-afferent sensory information can be used for predictive error processing. Therefore, the reliance on postdictive/external error processing becomes less important in the motor domain, especially in advanced stages of learning. All these factors might affect the temporal characteristics as well as the FRN amplitude in different ways. Some arguments would favor a hypothesis stating a lower FRN amplitude in the motor domain (1, 2), and other arguments would suggest a higher FRN amplitude in the motor domain (3, 4). Thus, no directional hypothesis has been stated. FRN latencies have been studied less frequently, as compared to amplitude measures. In general, latency measures reflect the temporal aspects of feedback processing (Lange et al., 2012; Luck, 2014), and the FRN latency is usually later when feedback comprises a higher cognitive load (Krigolson et al., 2012). With higher response complexity and ambiguity in motor tasks, the FRN latency should be further delayed in the motor domain than in the cognitive domain (5). However, the learnability of motor tasks as well as additional internal error processing might expedite the whole feedback processing as such and thus reduces the FRN latency (6).

Besides the emphasized domain-specific comparison, the present meta-analysis intends to reveal moderating factors of the FRN component within the motor domain. On the one hand, we analyzed those moderators, which influenced the FRN amplitude in previous cognitive studies (*feedback delay, feedback complexity, feedback modality*), while on the other hand, we looked at the moderators, which strongly varied in previous motor studies (*response complexity, assignment ambiguity, task type, number of trials*).

Foremost, it is assumed that *response complexity* is a relevant moderator, due to the higher range of different movement elements in motor tasks. Moreover, we scrutinize *feedback complexity* (cf., Cockburn & Holroyd, 2018; Colino et al., 2020; Mars et al., 2004) and *feedback delay* (cf., Arbel et al., 2017; Höltje & Mecklinger, 2020; Peterburs et al., 2016; Weinberg et al., 2012; Weismüller & Bellebaum, 2016) as moderators, as these have been shown to substantially affect feedback processing in the FRN interval in the cognitive domain. In motor tasks, *feedback complexity* can vary strongly, because here, feedback can focus on response selection and/or on action execution (Maurer et al., 2021). Low *feedback complexity* with a high feedback precision ambiguity (e.g., binary feedback) is assumed to induce higher FRN amplitudes, as compared to a high *feedback complexity* with low feedback precision ambiguity (e.g., quantitative feedback indicating direction and magnitude of the error). This has already been shown for cognitive tasks (e.g., time estimation task; Cockburn & Holroyd, 2018; Mars et al., 2004), as well as for a simple cursor pointing task (Colino et al., 2020). In experiments in the motor domain, the *feedback delay* varies between studies. In some studies, feedback is given immediately after movement execution (e.g., Aziz et al., 2020; Palidis et al., 2021; Reuter et al., 2020; cf., Table 1), while in other studies, it is provided with a certain temporal delay (e.g., De Bruijn et al., 2003; Joch et al., 2018a; Maurer et al., 2022; cf., Table 1). Shorter *feedback delays* of some hundred milliseconds (e.g., 500 ms) are assumed to induce higher FRN amplitudes as compared to longer *feedback delays* (e.g., 6500 ms in paired-associate learning; Arbel et al., 2017). Low feedback precision ambiguity and longer *feedback delays* seem to shift the burden of neural processing from reinforcement learning (as reflected in the FRN) to other learning mechanisms, such as supervised learning, which is reflected in other ERP components (Arbel et al., 2017; Cockburn & Holroyd, 2018; Margraf et al., 2022a, 2022b). Also, the *feedback modality* has been shown to significantly influence motor learning (Sigrist et al., 2013; Threadgill et al., 2020). For instance, Threadgill et al. (2020) postulated a higher FRN amplitude and a shorter FRN latency after auditory feedback as compared to visual feedback. The authors assumed that a higher FRN amplitude reflects a more pronounced RPE and a stronger and more pleasant reward signal with auditory feedback. The FRN latency was suggested to be shorter because auditory feedback might be discriminated faster than visual feedback (Liu & Gehring, 2009; Miltner et al., 1997; Threadgill et al., 2020).

1.4 | Specifics of a meta-analysis investigating event-related potentials

One challenge of a meta-analytic view on the FRN is the variety of different methodological approaches to measurement, such as interval vs. peak measurements or differences in intervals (e.g., Krigolson, 2018; Sambrook & Goslin, 2015; Williams et al., 2021). To enable a more homogeneous analysis, all activation-time series of the single data sets were reanalyzed with a unitary method, described as calculating Great Grand Averages (GGAs) in the meta-analysis of Sambrook and Goslin (2015). All activation-time curves (i.e., difference wave curves or grand average curves) of the single data sets were averaged to calculate the GGAs of all data sets that are integrated into the analysis. This approach is different from a common meta-analysis, since effect sizes are calculated as simple effect sizes, instead of standardized effect sizes (i.e., standardized mean difference). Standardized mean differences are normally warranted, as these enable the comparison of effects that are evaluated with different measures as dependent variables (e.g., centimeters and milliseconds). In this case, this is not necessary because the FRN amplitude is always measured in microvolts and the FRN latency in milliseconds (cf., Sambrook & Goslin, 2015).

The way the FRN is analyzed in motor studies and cognitive studies varies widely. Thereby, electrode position, intervals, and analysis procedures differ strongly. In this meta-analysis, we decided to follow the suggestions of Luck (2014), Williams et al. (2021), and others, by analyzing the mean difference wave, instead of a peak analysis. Using the mean difference wave has the following advantages: (1) that the data can be compared with other meta-analyses (Sambrook & Goslin, 2015; Stewardson & Sambrook, 2023), (2) that switches between FRN and RewP are easier to perform, and (3) that the problem of overlapping curves presented in the discussion is reduced. However, for a complete picture, the conditional waveforms and their GGA are also published in the supplementary material.

2 | METHOD

2.1 | Literature search, exclusion, and inclusion criteria

The literature was collected from the following databases: PsychArticles, PsychInfo, and Web of Science. The search was based on the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Moher et al., 2009). Thereby, the following keywords were combined with Boolean operators [“FRN” OR “feedback-related negativity” OR “feedback negativity” OR “reward positivity” OR “MFN”] AND [“error processing” OR “feedback”] AND [“motor” OR “movement” OR “motion” OR “sequence learning” OR “visuomotor adaptation” OR “finger sequence” OR “tracking” OR “serial reaction time”].

After removing duplicates, articles were analyzed by inclusion and exclusion criteria. Articles were included if the paper examined the FRN/RewP/MFN in consideration

TABLE 1 Overview of studies in the motor domain.

Experiment	N	Age	Site	Task	Number of trials	Task type[a]	Response complexity[b]	Feedback modality	Feedback delay	Feedback complexity	Precision ambiguity	Valence ambiguity	Assignment ambiguity
Armbrecht et al. (2012)	23	24.2 ± 1.0	FCz	Force production task	384	4	Low	Visual	1700 ms	Qual.	High	Low	High
Aziz et al. (2020); exp. 1)	18	19.5 ± 1.7	FCz	Prism adaption task	120	2	Low	Visual	0 ms	Quant.	Low	High	Low
Aziz et al. (2020; exp. 3)	22	19.7 ± 1.4	FCz	Prism adaption task	120	2	Low	Visual	0 ms	Quant.	Low	High	Low
Bediou et al. (2012)	16	22.8 ± 4.8	FCz	Computer-shooting task	376	3	Low	Visual	0 ms	Qual. & quant.	Low	Low	Low
Colino et al. (2017; old)	26	69.4 ± 2.2	FCz	Computer-based tracking task	30 × 2 min	3	High	Visual	0 ms	Qual. & quant.	Low	Low	Low
Colino et al. (2017; young)	26	21.4 ± 1.5	FCz	Computer-based tracking task	30 × 2 min	3	High	Visual	0 ms	Qual. & quant.	Low	Low	Low
Colino et al. (2020)	15	21 [19–25]	FCz	Simple pointing task	240	3	Low	Visual	400–600 ms	Quant. Qual.	High	Low	Low
De Bruijn et al. (2003)	18	18–25	Cz	Four-choice isometric-force production task	800	4	Low	Visual	1000 ms	Qual.	High	Low	Low
Frömer et al. (2016)	68	24 ± 5	Fronto-central ROI	Computerized darts throwing task	315	1	Low	Visual	Delayed	Qual. & quant.	Low	Low	Moderate
Grand et al. (2017)	70	21.7 ± 2.1	Fz	Underhand beanbag tosses	100	1	Low	Visual	Delayed	Qual. & quant.	Low	Low	Moderate
Joch et al. (2017)	21	22 ± 2.3	FCz	Semivirtual throwing task	800	1	Low	Bimodal	850 ms	Qual. & quant.	Low	Low	Moderate
Joch et al. (2018a)	20	22.5 ± 4.5	FCz	Semivirtual throwing task	390	1	Low	Bimodal	1500 ms	Qual. & quant.	Low	Low	Moderate
Joch et al. (2018b)	17	21.7 ± 4.2	FCz	Semivirtual throwing task	860	1	Low	Bimodal	850 ms	Qual. & quant.	Low	Low	Moderate
Krause et al. (2020)	24	22.1 ± 3.4	FCz	Arm-movement sequence task	192	3	High	Visual	2500 ms	Qual. & quant.	High	Low	High
Liu et al. (2021)	20	25 ± 4.28	Cz	VR trap-shooting task	1440	3	Low	Visual	0 ms	Quant. & qual.	Low	Low	Moderate
Loehr et al. (2015)	22	24.2 ± 3.1	FCz	Sequence production task of tones	360	3	High	Visual	700 ms	Qual.	High	Low	Low
Margraf et al. (2022a, 2022b)	38	20.8 [18–26]	FCz	Arm-movement sequence task	960	3	High	Visual	2500 ms	Qual. & quant.	High	Low	High

(Continues)

TABLE 1 (Continued)

Experiment	N	Age	Site	Task	Number of trials	Task type[a]	Response complexity[b]	Feedback modality	Feedback delay	Feedback complexity	Precision ambiguity	Valence ambiguity	Assignment ambiguity
Maurer et al. (2019)	21	22 ± 2.3	FCz	Semivirtual throwing task	1200	1	Low	Bimodal	850 ms	Qual. & quant.	Low	Low	Moderate
Maurer et al. (2022)	19	22.9 ± 4	FC1, FCz, FC2	Semivirtual throwing task	4000	1	Low	Bimodal	800 ms	Qual. & quant.	Low	Low	Moderate
Mushtaq et al. (2022)	29	26.8 ± 9.5	FC1, FCz, FC2	Three-armed bandit reaching task	400	3	Low	Visual	1000 ms	Qual. & quant.	Low	Low	Low
Palidis et al. (2019)	20	23.2 ± 3.1	FCz	Visuomotor rotation task	500	2	Low	Visual	0 ms	Qual.	High	Low	Low
Palidis et al. (2019; reward learning)	17	21.0 ± 3.3	FCz	Reaching adaptation via reward learning	250	2	Low	Visual	0 ms	Qual.	High	Low	Low
Reuter et al. (2017; old)	24	69.7 ± 4.3	FCz	Force field adaption task with reaching movements	600	2	Low	Bimodal	0 ms	Qual. & quant.	Low	Low	Low
Reuter et al. (2017; young)	25	19.0 ± 2.0	FCz	Force field adaption task with reaching movements	600	2	Low	Bimodal	0 ms	Qual. & quant.	Low	Low	Low
Reuter et al. (2020; young)	19	21.3 ± 4.1	FCz	Force field adaption task with reaching movements	320	2	Low	Bimodal	0 ms	Qual. & quant.	Low	Low	Low
Reuter et al. (2020; old)	17	69.2 ± 2.9	FCz	Force field adaption task with reaching movements	320	2	Low	Bimodal	0 ms	Qual. & quant.	Low	Low	Low
Torrecillos et al. (2014)	15	24.6 [21–35]	FCz	Force field adaption task with reaching movements	1200	2	Low	Visual	0 ms	Qual.	High	Low	Low
Trska (2018)	17	21.2 [19.7–22.7]	FCz	Drawing task	450	3	Low	Visual	400–600 ms	Qual.	High	Low	Low

Note: Experiments used in the meta-analysis including the number of participants, age, electrode site, task and task type, response complexity, feedback modality, feedback delay, feedback complexity with valence ambiguity, precision ambiguity, and assignment ambiguity.

[a] (1) spatial precision tasks with goal-directed throwing (force parameterization and spatial precision), (2) spatial precision tasks with visuomotor adaption, (3) spatial precision tasks without goal-directed throwing or visuomotor adaptation, (4) force production tasks where force parameterization was required.

[b] Response complexity refers to the number of successive elements.

of valence dependency, and the experimental task could be categorized as a motor task with feedback provided for the execution or outcome of the motor task. The data set must contain ERPs at least for two levels of outcome accuracy (e.g., qualitative hits vs. miss/ reward vs. loss; or quantitative higher vs. lower accuracy/ higher reward vs. lower reward). Waveforms had to be plotted for at least 50 ms prior feedback onset and 450 ms post feedback on a frontal/ central site (at electrode position Fz, FCz, or Cz, or on fronto-central ROI). If the EEG signals for more electrodes were published, we preferred FCz, followed by Fz and Cz. Participants of all ages were included. Studies in which no feedback was provided on movement execution or movement outcome, such as studies in which movement responses were given for decision-making, were excluded. Further, the reference lists of all studies included were double-checked for additional papers. The literature search was finalized on February 15, 2023.

Finally, 25 studies were included in the present meta-analysis and 28 data sets were analyzed (Figure 1). The higher number of data sets originates from different experimental groups within some studies (e.g., different age groups, see study overview). If studies had more than one experimental condition (i.e., frequent vs. infrequent/valid vs. invalid/quantitative vs. qualitative feedback), the average of both ERP curves was calculated and used for further analysis. There was one exception to this rule: In the moderator variable analysis, the experimental groups (quantitative vs. qualitative feedback) of Colino et al. (2020) were used separately when analyzing the moderator *feedback complexity*. Data sets with deviating FRN latencies were not excluded because latencies vary a lot in motor studies (Colino et al., 2017; Grand et al., 2017; Maurer et al., 2021; Torrecillos et al., 2014), and it was of special interest to reflect this temporal variability of the FRN in motor tasks. Studies with a very short FRN latency were double-checked, and for the two studies the ERN amplitude was also presented (Colino et al., 2017; Maurer et al., 2022) to clarify that the component was indeed the FRN and not the ERN.

2.2 | Moderator variables

Several moderating factors for the FRN have been analyzed in the cognitive domain (e.g., *feedback delay*, *feedback complexity, number of trials*), while other factors are known to affect motor learning and the underlying cognitive processes in general (e.g., *type of task*, *response complexity*). We were therefore interested in whether these moderators also affect the FRN amplitude and the FRN latency in the motor domain.

2.2.1 | Feedback delay

The *feedback delay* defines the time interval between movement offset and feedback onset. While a *feedback delay* of some hundred milliseconds seems to be necessary

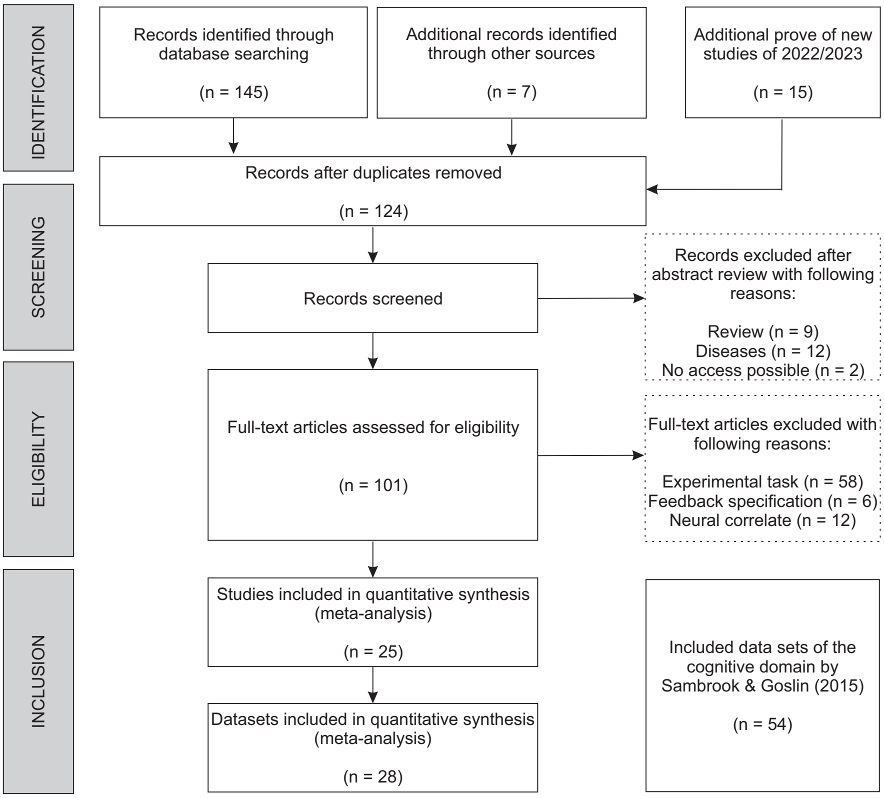

FIGURE 1 Prism diagram (modif. Moher et al., 2009).

for the FRN to be fully observable (Bismark et al., 2013), several studies also used immediate feedback presentation (e.g., Aziz et al., 2020; Bediou et al., 2012; Colino et al., 2017). Short *feedback delays* of some hundred milliseconds (e.g., 500 ms) elicited higher FRN amplitudes as compared to longer *feedback delays* (e.g., 6500 ms) in cognitive tasks (Arbel et al., 2017; Höltje & Mecklinger, 2020; Weinberg et al., 2012; Weismüller & Bellebaum, 2016; for a review: Hinneberg & Hegele, 2021). Additionally, it has been revealed that the FRN amplitude decreases linearly across increasing delay durations (500 ms; 3500 ms; 6500 ms; Hinneberg & Hegele, 2021). Foerde and Shohamy (2011) demonstrated that consistent with these FRN-related delay effects, the striatum, as a neural substrate involved in reinforcement learning, shows a higher activation under short *feedback delay* conditions, while the hippocampus is more strongly activated when the feedback is delayed. The hippocampus is well known for connecting temporal gaps between events to link information (Levy & Sederberg, 1997; Wallenstein et al., 1998). This suggests, that with a delay of feedback, the underlying mechanisms shift from prediction error-based, non-declarative learning (i.e., reinforcement learning) to declarative learning mechanisms (Foerde & Shohamy, 2011).

Weismüller and Bellebaum (2016) summarized that most ERP studies used immediate feedback or feedback delay intervals of less than one second, rather than delayed feedback of longer intervals (see, e.g., Bellebaum & Daum, 2008; Ferdinand et al., 2012; Hajcak et al., 2007; Holroyd & Coles, 2002). Hinneberg and Hegele (2021) presented six studies investigating the FRN with time delays of around 6000 ms. Within this meta-analysis, 14 studies with immediate, 11 studies with short delay of 400–1700 ms, 2 studies with 2500 ms delay, and 2 studies with unspecified delay could be summarized. Reasonably, FRN latency effects are expected to be shorter than in studies comparing short and long feedback delays (Arbel et al., 2017; Hinneberg & Hegele, 2021; Höltje & Mecklinger, 2020; Weinberg et al., 2012; Weismüller & Bellebaum, 2016).

2.2.2 | Feedback modality

Already Miltner et al. (1997) used different feedback modalities in their first study when examining the ERN and the FRN. They revealed that both correlates (the ERN and the FRN) were evoked independent of the feedback modality (visual, auditory, or somatosensory), while the FRN latency was shorter after auditory than after visual feedback. Although most previous studies used visual feedback (cf. Table 1), there are a few studies, which also implemented auditory (e.g., Batavia et al., 2001; Petrofsky, 2001), haptic (e.g., Ruffaldi et al., 2009; van Erp & van Veen, 2004), or multimodal (e.g., Sun et al., 2011) augmented feedback (cf., review Sigrist et al., 2013). Threadgill et al. (2020) reported a shorter FRN latency when feedback in a door-choosing task was provided with auditory stimuli compared to visual feedback stimuli. It was argued that auditory feedback can be discriminated faster than visual feedback, which increases feedback processing speed and thus leads to a decreased FRN latency. Hence, the factor *feedback modality* seems to be a possible moderator of the FRN latency, worth to be analyzed for all studies included in this meta-analysis.

2.2.3 | Task type

Experimental tasks were categorized as follows: (1) spatial precision tasks with goal-directed throwing (force parameterization and spatial precision), (2) spatial precision tasks with visuomotor adaptation, (3) spatial precision tasks without goal-directed throwing or visuomotor adaptation, and (4) force production tasks in which force parameterization was required. Especially, motor adaptation tasks (belonging to the second category) and sequence learning tasks (belonging to the third category) differ from each other because of different underlying neural mechanisms and strategic processes (Caligiore et al., 2019; Debas et al., 2010; Doyon et al., 2003; Seidler et al., 2013).

2.2.4 | Response complexity

Response complexity might be a significant moderator due to the high range of *response complexity* in the motor domain and the assumption that *response complexity* modulates the complexity of feedback processing. To our knowledge, this assumption has not been tested experimentally so far. *Response complexity* was classified as high if more movement elements had to be executed sequentially in the task (e.g., a sequence of flexion and extension of a joint or sequence of elements with different joints, such as in piano playing) (e.g., Krause et al., 2020; Margraf et al., 2022a, 2022b). A higher FRN latency was hypothesized for more complex responses due to a higher cognitive load in tasks with a larger number of elements (Krigolson et al., 2012).

2.2.5 | Feedback complexity

In this meta-analysis, *feedback complexity* focuses on the amount of information, which must be processed to integrate feedback information. This is distinct from other studies focusing more on the stimulus complexity and size, which also influenced the FRN amplitude with an increased FRN for more complex (positive) stimuli (Pfabigan et al., 2015, 2019). Here, *feedback complexity* is differentiated into three levels: first, for pure qualitative feedback conditions (e.g., binary feedback as win vs. loss). This kind of feedback is characterized by a low valence ambiguity and a high precision ambiguity. According to the low valence ambiguity in conditions with qualitative feedback, the FRN amplitude is expected to be higher (Cockburn & Holroyd, 2018; Colino et al., 2020; Mars et al., 2004), reflecting a high involvement of reinforcement learning. Krigolson et al. (2012) revealed that a less direct coding of valence (valence was coded in the sum of two numbers being odd or even) substantially reduced the FRN amplitude compared to an unambiguous direct binary coding of valence. The latter finding seems to be caused by an increased variability of the FRN latency. Second, for feedback of a low valence ambiguity and a low precision ambiguity, resulting from a combination of qualitative and quantitative feedback information. Here, participants receive information about the qualitative level of success (e.g., win vs. loss) and quantitative error information about the movement execution simultaneously. For example, if bandwidth feedback with a combination of qualitative and quantitative information is used (e.g., reward is given for small errors below a certain bandwidth, but the magnitude and direction of the error are also reported to the learner; e.g., Krause et al., 2020; Margraf et al., 2022a, 2022b).Third, feedback that provides precise quantitative feedback information but misses valence information. Thus, valence ambiguity is high and precision ambiguity is low. This last category should elicit the lowest FRN amplitude, as quantitative feedback induces other mechanisms of feedback processing (e.g., supervised learning; Arbel et al., 2013).

2.2.6 | Feedback assignment ambiguity

Feedback assignment ambiguity is categorized as high if feedback is not obviously assigned to a specific element of a task. For example, if only knowledge of results is given, it can be difficult to assign, which movement element caused a given error in the outcome of complex movements (Winstein et al., 1994). This problem is known as the credit assignment problem (e.g., Fu & Anderson, 2008; Rothkopf & Ballard, 2010). A dart hitting a dartboard too high can result from a certain combination of a too early release of the dart and too high takeoff speed. So far, *assignment ambiguity* does not seem to be an established research topic in the cognitive domain, while it is discussed to affect the FRN amplitude by some authors in the motor domain (Krause et al., 2020; Margraf et al., 2022a, 2022b). Higher *assignment ambiguity* might increase the variability of the FRN latency between trials, as cognitive load is lower when feedback for a certain trial is easy to assign to a particular task element and the FRN latency is shorter, whereas the FRN latency is longer when the assignment in a certain trial is more difficult. A higher variability of the FRN latency would lead to a lower FRN amplitude, as it was found for a higher latency variability according to a less direct mapping of feedback valence (Krigolson et al., 2012).

2.2.7 | Learning rate/number of trials

One difference between studies from the cognitive domain and studies in the motor domain is the learnability of tasks. Maurer et al. (2022) postulated that during the learning progress, FRN amplitudes decrease and ERN amplitudes (responsible for internal error processing) increase. It can therefore be predicted that in motor learning tasks, FRN amplitudes should be lower when averaged over a whole experiment compared to cognitive tasks, since amplitudes decrease over the course of the experiment as learning occurs. Nevertheless, after categorization of the studies included, we must emphasize that the number of trials in these experiments was on average 634.5 ± 634.67 trials. This strongly deviated from the 4000 trials in the study of Maurer et al. (2022), who found crossing effects of both neural correlates that mean a reduction of the FRN amplitude. The pre-analysis of a possible influence of the number of trials on the FRN amplitude via a scatter plot did not reveal any sign of correlation, so the number of trials was not further included in the moderator variable analysis.

2.3 | Data analysis

2.3.1 | Data processing

The GGA technique, first used in the meta-analysis by Sambrook and Goslin (2015), was utilized for data analysis. To this end, the published waveforms of all studies were digitized with the software Plot Digitizer (http://sourceforge.net/projects/plotdigitizer/), and after calibrating x and y axes, the waveforms were touchpad-clicked in approximately 5 ms intervals. Sambrook and Goslin (2015) provided access to their supplementary materials, enabling us to adjust and reuse the *Interpolate* Microsoft Excel file of their study for interpolating the clicked data from irregular intervals in fixed 1 ms intervals.

To ensure accuracy of the touchpad-clicked data, waveforms were replotted after construction and compared with the plots of the original studies, respectively. To avoid minor inaccuracies in the curves clicked, the moving average of the surrounding five data points was used to smooth the curves. The waveforms of the cognitive domain were taken from the published Microsoft Excel files of Sambrook and Goslin (2015) and were reanalyzed for the purpose of the present meta-analysis. The following data analysis was performed with Microsoft Excel (16.48, 2021, Microsoft Corporation, Redmond, USA), with the IBM Statistical Package for the Social Science (SPSS; 28, 2020, SPSS Inc., Chicago, IL, USA), and with MathWorks MATLAB (R2021, MathWorks, Natick, MA, USA).

In most studies, the FRN difference wave was already published. Sometimes the published wave had to be inverted or self-calculated to obtain a homogeneous difference wave (negative feedback-related minus positive feedback-related conditional curve). The FRN amplitude was calculated as the average of the difference wave within the time window of 25 ms before and after the maximum amplitude peak of each individual difference wave. To do this, we first plotted the difference wave of each study and calculated the maximum of the difference wave and its time point. An interval of ±25 ms around this maximum peak was then used to calculate the mean FRN amplitude of each individual study. Mean FRN amplitudes were later averaged to get the GGA of the FRN amplitude for the motor domain and for the cognitive domain. This was done because of the large heterogeneity and the problem of overlapping curves of studies in the motor domain (cf. discussion). The FRN latency was determined as the time point of the maximum amplitude peak of the difference wave in the FRN time window.

2.3.2 | Statistics

In contrast to common meta-analyses, effect sizes were calculated as simple effect sizes instead of standardized effect sizes (i.e., standardized mean difference). A standardized effect size is often used to permit the synthesis of measures in different units, which is not necessary here, as ERPs are commonly reported in microvolts (cf., Sambrook & Goslin, 2015). Weighted *t* tests were conducted using grand average data instead of subject average data. In line with Sambrook and Goslin (2015), the sample sizes of the individual studies were used as weighting for inclusion in the meta-analysis. Therefore, the variable was multiplied by the study's sample size, and the sum of all studies was built and divided by the overall sample size of all studies included (Hunter & Schmidt, 2004; Sambrook & Goslin, 2015). It was argued that this allows the best comparison when using the GGA technique (cf., Sambrook & Goslin, 2015). For all tests, normal distribution and variance homogeneity (Levene's test) were tested, and corresponding independent two-sample *t* test for variance homogeneity or heterogeneity were used. Valence differences within one domain were calculated by paired-sample *t* tests. A one-sample *t* test was used for the comparison of the FRN amplitude against zero.

To analyze any differences between moderator variables, one-way ANOVAs of FRN amplitudes and FRN latencies were used for all moderators as single factor. In addition, the weighted least squares function for the variable *sample size* was used in IBM SPSS statistics to ensure weighting for studies in ANOVAs. The alpha level was set to .05 for all statistical analyses. All results are given as mean values and standard deviations. The partial eta squared (η_p^2) or Cohen's *d* were calculated as effect sizes of the statistical tests performed.

3 | RESULTS

3.1 | FRN amplitude

A weighted one-sample *t* test on the FRN amplitude against zero confirmed a significant difference in the weighted FRN amplitude ($M = -3.59\,\mu V$, $SD = 1.81\,\mu V$) in the motor domain, $t_{28} = -11.25$; $p < .001$; $d = 2.13$. A weighted independent two-sample *t* test revealed a significant difference between the weighted FRN amplitude of the motor domain and the weighted FRN amplitude of the cognitive domain ($M = -2.69\,\mu V$, $SD = 1.61\,\mu V$), $t_{81} = 2.31$; $p = .001$; $d = 0.54$ (Figure 2a). Figure 2b shows the weighted GGA curve of the FRN for both domains. A two-sample *t* test also revealed a significant difference in both waveforms for the whole interval of −50 to 450 ms, $t_{500} = 2.55$; $p = .011$; $d = 0.23$.

3.2 | FRN latency

Weighted independent two-sample *t* tests revealed a significant difference in the FRN latency between the motor domain ($M = 257.18$ ms, $SD = 42.66$ ms) and the cognitive domain ($M = 276.48$ ms, $SD = 26.73$ ms), $t_{81} = 2.19$; $p = .032$; $d = 0.59$. Interestingly, the weighted Levene's test showed heterogenous variances of the FRN latencies for both domains, with a higher variance in the motor domain than in the cognitive domain ($p < .001$) (Figure 2c).

3.3 | Outliers and publication bias analysis

In research, studies with significantly large effect sizes are favored to get published as compared to data sets with

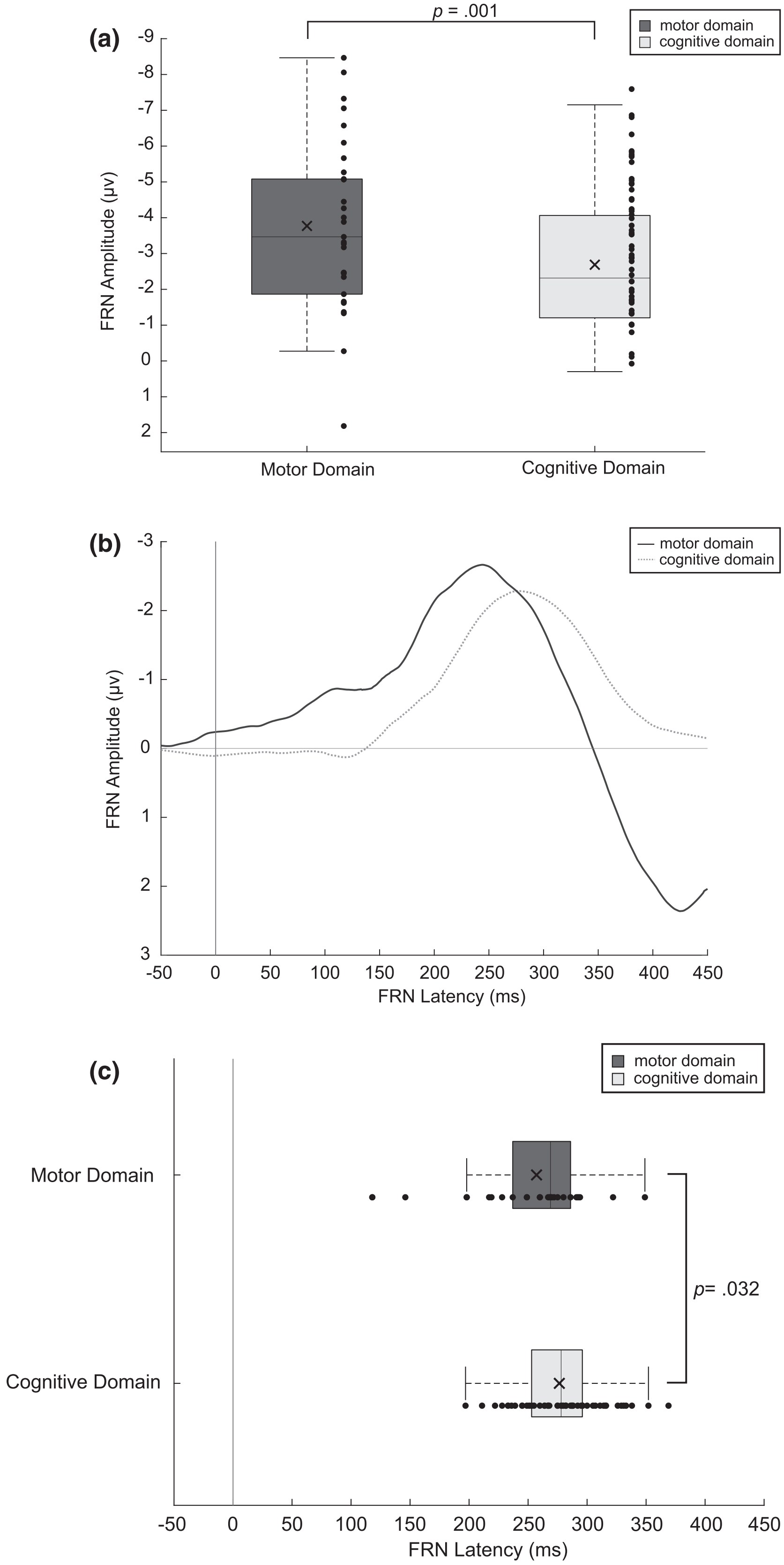

FIGURE 2 Comparison of (a) feedback-related negativity (FRN) amplitude, (b) Great Grand Average curves, (c) FRN latency between motor domain (dark) and cognitive domain (light).

smaller effects or null results. This can lead to systematic errors and exaggeration of effects in meta-analyses. Analyses of publication biases help to assess the risk of unpublished or undiscovered results to the validity of a meta-analysis (Shi & Lin, 2019). To check whether a publication bias is present, forest plots and funnel plots can be analyzed. Forest plots represent the distribution of included effect sizes. Mean differences in each study are plotted with its weighting (in this meta-analysis: the sample size). The diamond shows the overall effect estimate of the meta-analysis with its 95% confidence intervals (Chang et al., 2022). In a forest plot, the statistical significance is visually analyzed with the vertical line (in Figures 3 and 4). If the confidence interval of the dependent variable excludes the null effect, it is indicated that the difference against zero is significant. Also, it can be seen how many studies are near-null results. Heterogeneity of studies can be visually inspected with *the eyeball analysis* (Verhagen & Ferreira, 2014). We further investigated variance heterogeneity with Levene's test for homogeneity of variances.

Figure 3 represents a forest plot for the FRN amplitude in the motor domain, while Figure 4 illustrates one for the FRN amplitude in the cognitive domain. Figure 5 shows a forest plot for the FRN latency in the motor domain and Figure 6 for the FRN latency in the cognitive domain. By visual inspection, the overall effect size of the FRN amplitude as well as the individual effect sizes of all studies in the motor domain differed from an estimated null effect. De Bruijn et al. (2003) was the only

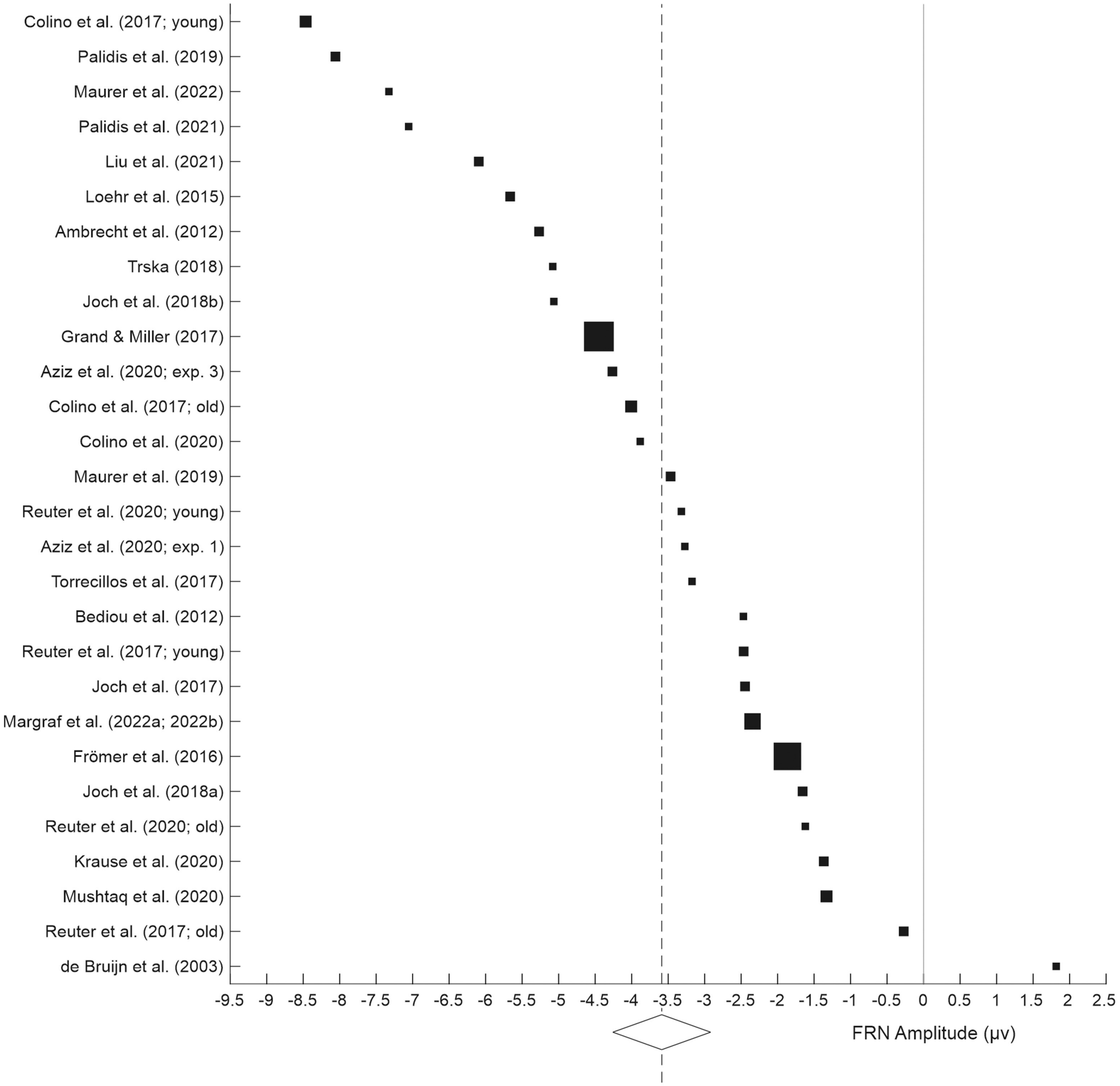

FIGURE 3 Forest plot for simple effect sizes presented by feedback-related negativity amplitude of all included studies in the motor domain.

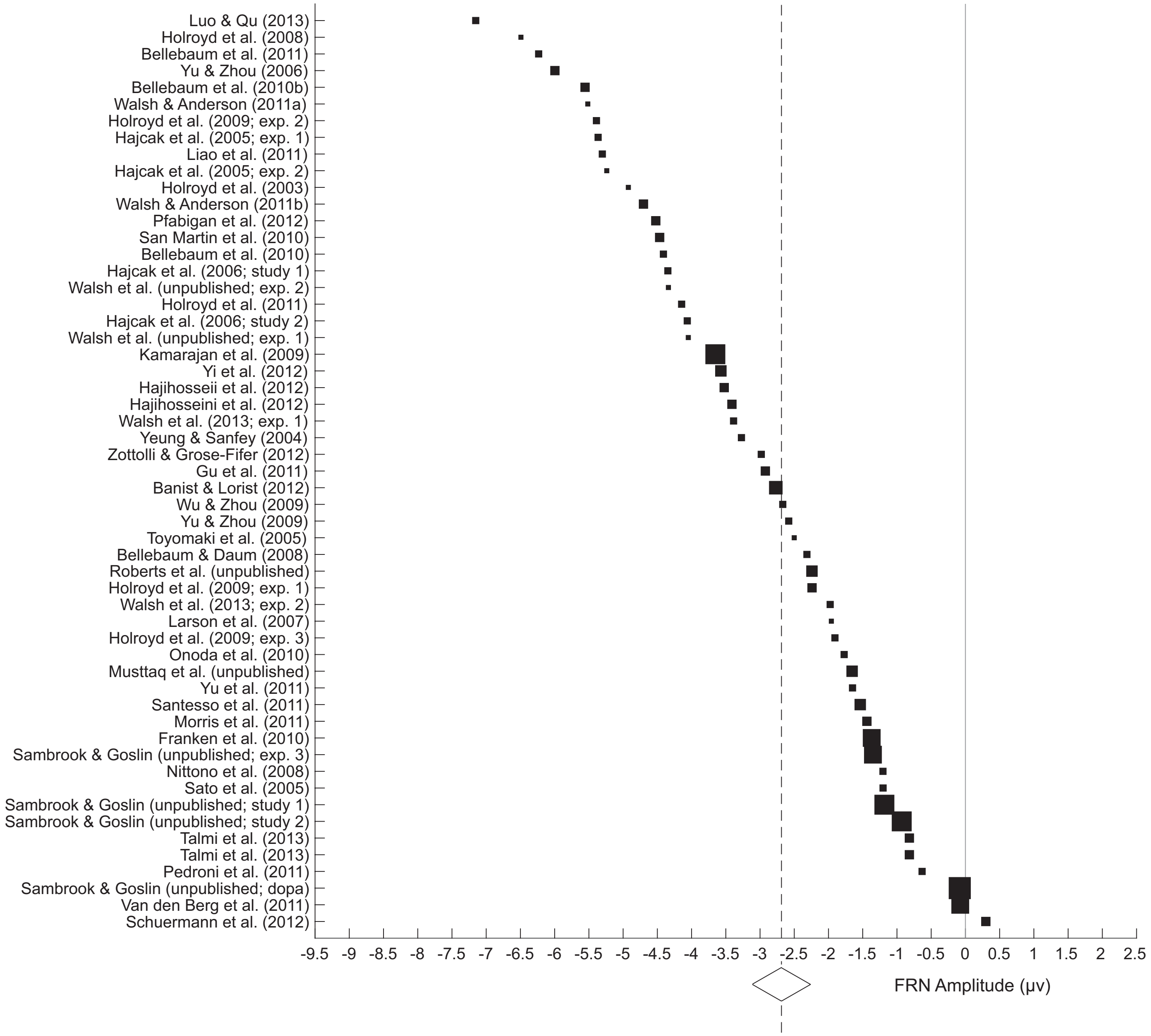

FIGURE 4 Forest plot for simple effect sizes presented by feedback-related negativity amplitude of all included studies in the cognitive domain.

study, whose FRN amplitude was positive, which might be induced by a positivity after the FRN component that was larger in negative feedback conditions. When comparing the diamonds of Figures 3 and 4 between studies in the motor domain with the cognitive domain, the FRN amplitudes were of a larger heterogeneity in the motor domain. This was confirmed by Levene's test of variance homogeneity.

Figure 5 presents the forest plot for the FRN latency in the motor domain. Against the expectations of an FRN latency of 150–400 ms that was based on the previous meta-analysis in the cognitive domain (Sambrook & Goslin, 2015), the variation of the FRN latency in the motor domain was even higher. For visual inspection, most studies showed a maximum negative activation of about 200–300 ms, but some studies deviated from this, for example, Colino et al. (2017) and Maurer et al. (2022), which showed shorter latencies of less than 100 ms. Both studies differentiated the FRN from the ERN component and presented both components in their studies, which excludes a possible misinterpretation of the ERN as an FRN. The shorter latency may have depended on the specific experimental settings. In both tasks, early availability of additional extrinsic information for outcome prediction (e.g., visible flight path of a thrown object) might shorten the time for processing the prediction error because the final outcome is already primed by this prior information. Future studies should scrutinize, if certain sources of information prior to the outcome feedback

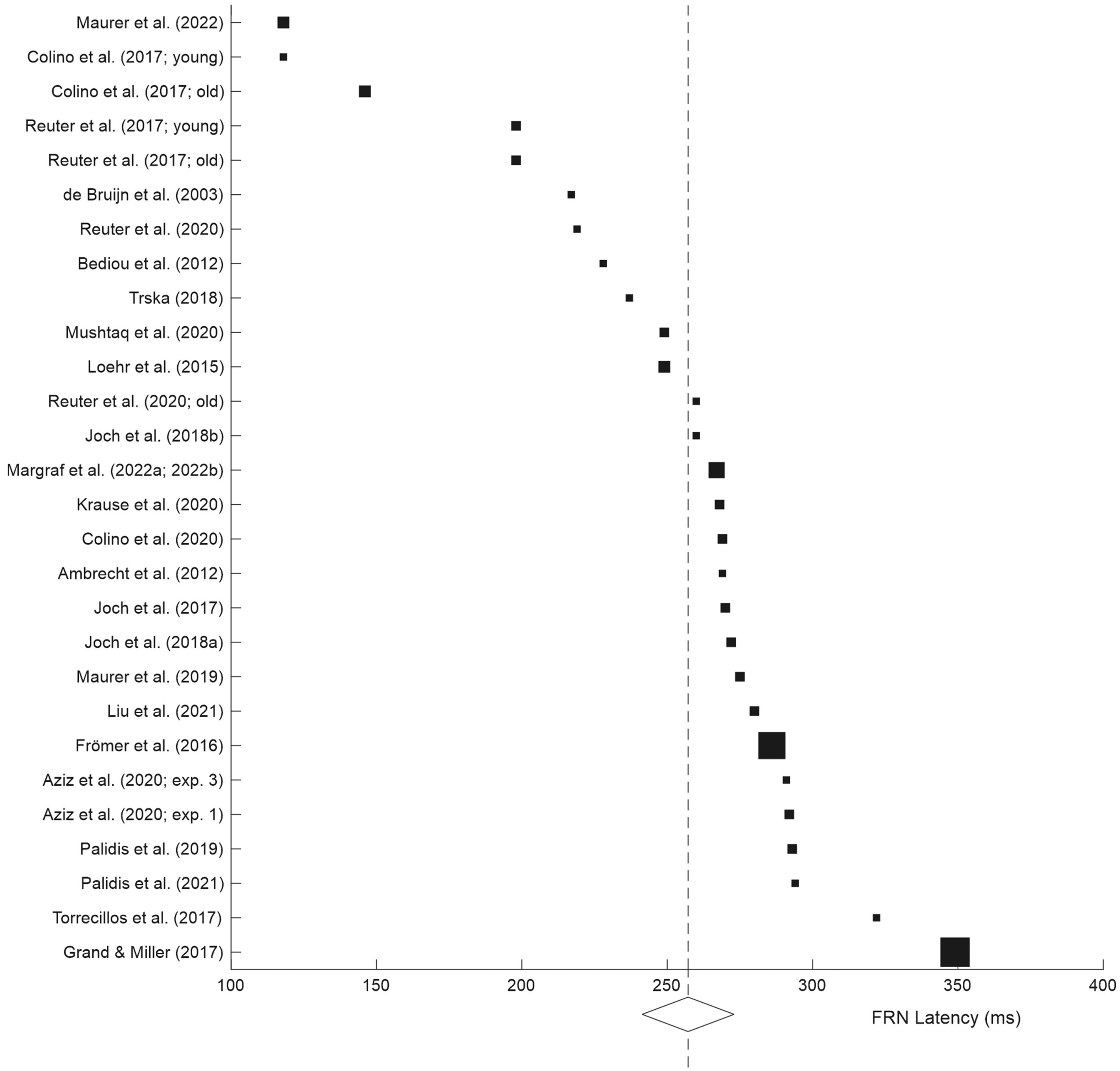

FIGURE 5 Forest plot for simple effect sizes presented by feedback-related negativity latency of all included studies in the motor domain.

might speed up processing of feedback and thus reduce respective latencies.

Figure 7 presents the funnel plots for the components investigated in this study. A funnel plot is a scatterplot that shows the effect sizes of individual studies against each study's sample size. It is argued that studies with smaller sample sizes vary more around the true effect size, while studies with larger sample size scatter less. The estimated mean of all effect sizes is plotted with a horizontal line, while on each side of the estimated effect size, an extending 1.95 standard error is presented. All studies should fall within this standard error range and be equally distributed (Sterne et al., 2011).

Visual inspection did not indicate strong asymmetries in the FRN amplitude in the motor domain (Figure 3) or in the cognitive domain (Figure 4). Studies with small or large sample sizes were not more likely to be outliers, and the outliers were equally distributed for over- and under-estimating the mean difference. Figure 7b presents a funnel plot for the FRN latency. By visual inspection, several outliers with very short or very long FRN latencies can be observed. However, most studies varied between the estimated ranges of the effect size, so we did not expect a wrong estimate of the mean FRN latency. Although a publication bias might exist, such that authors using motor tasks might have analyzed time ranges just between 200 and 300 ms, as presented in previous

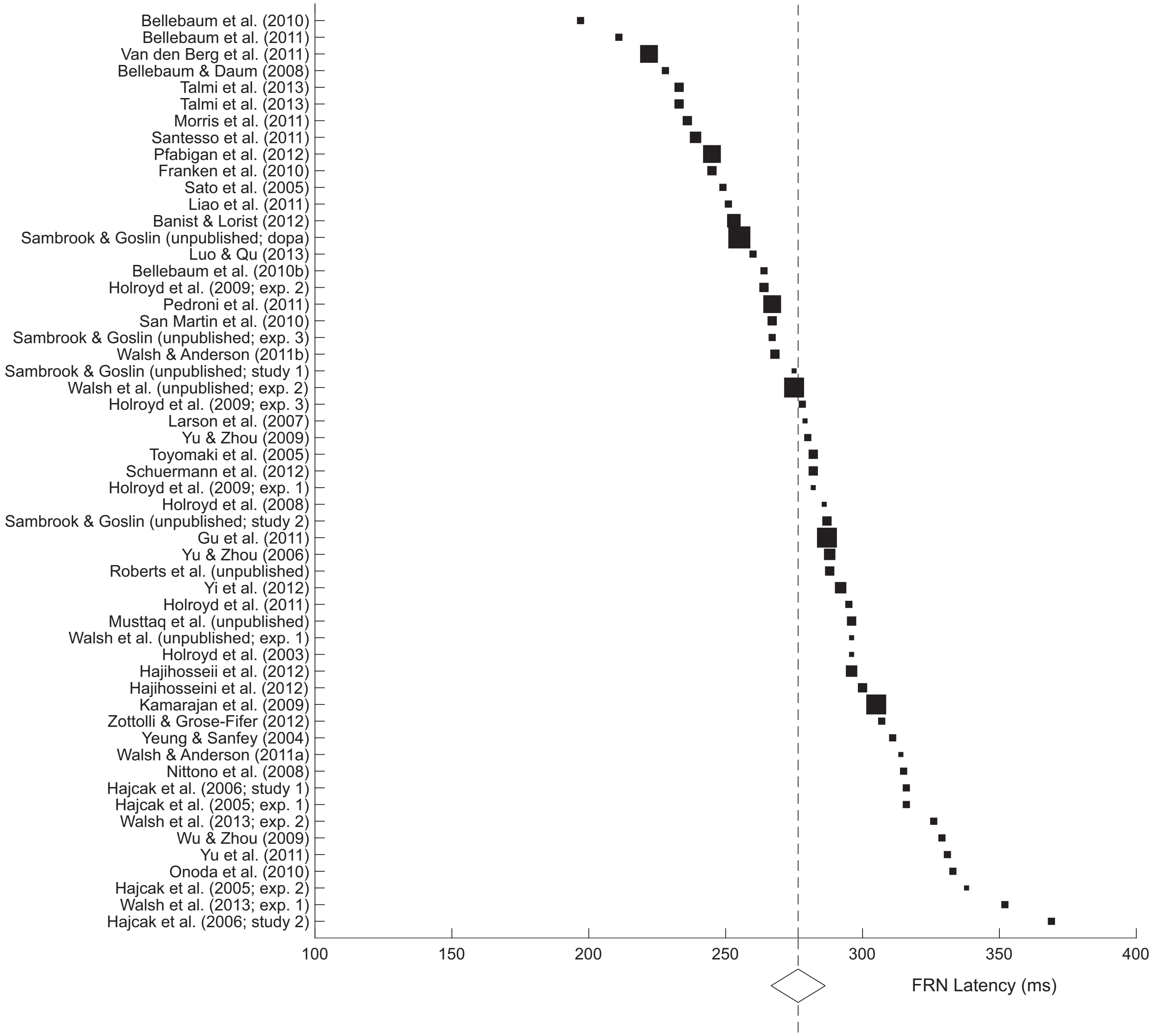

FIGURE 6 Forest plot for simple effect sizes presented by feedback-related negativity latency of all included studies in the cognitive domain.

studies (e.g., Holroyd & Coles, 2002; Miltner et al., 1997). Consequently, they may not have found the FRN component in these time periods and thus did not publish their data or define a respective FRN occurring in a different time period as a different component.

3.4 | Moderator analysis for studies in the motor domain

The ANOVAs for the weighted least square function did not identify a moderator variable to significantly moderate the FRN amplitude (Table 2). The moderator variable *feedback modality* ($M_{\text{visual}} = 273.34$ ms, $SD_{\text{visual}} = 11.42$ ms; $M_{\text{bimodal}} = 227.31$ ms, $SD_{\text{bimodal}} = 18.74$ ms) moderated the FRN latency significantly, $F_{26} = 4.40$, $p = .046$, $\eta_p^2 = .15$, with a shorter FRN latency after combined auditory and visual feedback than after pure visual feedback (Table 3).

4 | DISCUSSION

The present meta-analysis scrutinized the FRN amplitude and the FRN latency in the motor domain, in order to compare it to meta-analytic findings previously reported for the cognitive domain (cf., Sambrook & Goslin, 2015) and to reveal potential moderating factors within the motor domain. In a systematic literature search, 25 studies

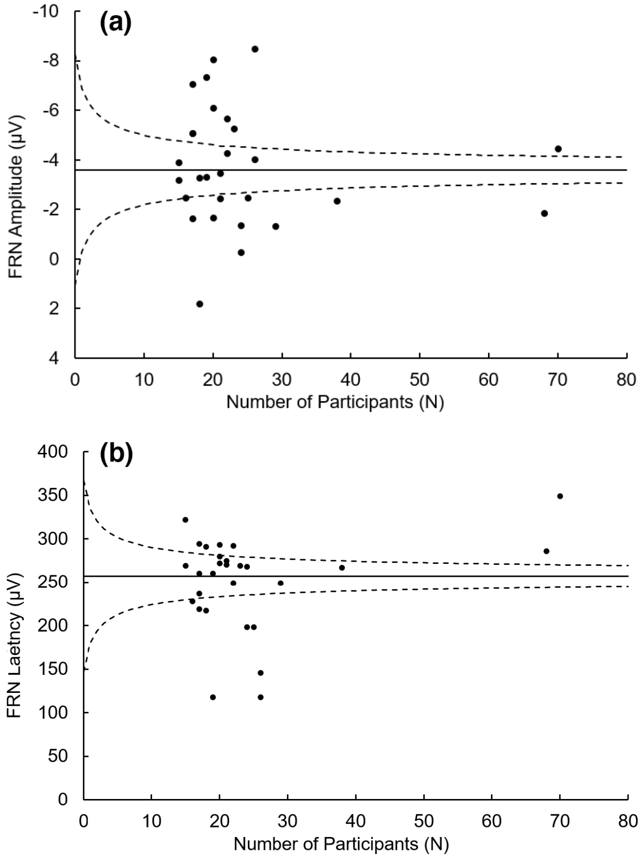

FIGURE 7 Funnel plots for (a) feedback-related negativity (FRN) amplitude and (b) FRN latency of the motor domain.

(with overall 28 data sets) were identified within the motor domain. These were compared to the meta-analysis of 47 studies (with overall 55 data sets) in the cognitive domain by Sambrook and Goslin (2015).

For the moderator analysis, the studies of the motor domain were classified according to the variables *feedback delay*, *feedback modality*, *task type*, *response complexity*, *feedback complexity*, *assignment ambiguity*, and *trial number* because of the assumed moderating effects of these variables on the FRN amplitude and the FRN latency (e.g., Arbel et al., 2017; Cockburn & Holroyd, 2018; Colino et al., 2020; Gibbons et al., 2016; Hinneberg & Hegele, 2021; Höltje & Mecklinger, 2020; Liu & Gehring, 2009; Mars et al., 2004; Maurer et al., 2022; Paul et al., 2020; Peterburs et al., 2016; Weinberg et al., 2012; Weismüller & Bellebaum, 2016). We decided to focus on the FRN as terminology because it is more established in the motor domain, and it can be better used for a comparison between the FRN (external postdictive feedback processing) and the ERN component (internal predictive feedback processing), which are both crucial neural signatures in motor learning (Maurer et al., 2021).

In accordance with the vast majority of studies (e.g., Holroyd & Coles, 2002; Miltner et al., 1997; Nieuwenhuis et al., 2002; San Martín, 2012; Sato et al., 2005; Seidler et al., 2013; Yeung et al., 2005), a larger negativity was found after negative feedback than after positive feedback, which was statistically reflected in a significant difference of the FRN difference measure against zero. This valence effect was also revealed in the previous meta-analysis by Sambrook and Goslin (2015).

4.1 | Discussion FRN amplitude

The domain-specific comparison confirmed the hypothesis that the FRN amplitude was higher in the motor domain than in the cognitive domain. Thus, responses on RPEs seem to be stronger in the motor domain as compared to the cognitive domain. Following the interpretation of the FRN component as a RewP (Krigolson, 2018; Peterburs et al., 2016), the data would also suggest that reward-related processing is more pronounced in the motor domain than in the cognitive domain.

As explained in the introduction, in many task settings, motor tasks are of a higher complexity than cognitive tasks because of a larger number of elements (simultaneous and successive), and thus higher degrees of freedom of body parts must be coordinated. This renders reward predictions more sophisticating and reward feedback becomes more ambiguous. This is strengthened by the way feedback is assigned to errors in motor tasks. Errors in cognitive tasks are commonly assigned to action selection for highly automatized (and simple) button presses. In contrast, errors in motor tasks can arise for different task elements during action selection, as well as during movement execution (De Bruijn et al., 2003; Maurer et al., 2021; Mushtaq et al., 2022). For example, when throwing a ball to a specific target, the wrong target could have been chosen, but missing the target could also be induced by a wrong release point, a wrong estimation of the ball's flight curve, the distance to the target area, the control of the muscular system, the wrong standing position, a slippery surface, etc. It has been shown that feedback focusing on execution errors induces higher FRN amplitudes compared to feedback that is related to selection errors (Mushtaq et al., 2022). This supports the present finding that the FRN amplitude was higher in motor tasks, where feedback is related to movement execution (and action selection) than in cognitive tasks, where feedback is related exclusively to action selection.

Mushtaq et al. (2022) argued that the higher FRN amplitude following execution errors could also be explained by a higher amount of agency following these errors, such that participants assume a higher level of control during action execution errors. In addition, errors are divided into low-level errors and high-level errors. Low-level errors

TABLE 2 Moderator variable analysis of feedback-related negativity amplitude with weighted descriptive statistics.

	Descriptive statistics			ANOVA		
Moderator variables	***K***	***M* (μV)**	***SD* (μV)**	***F***	***p***	η_p^2
Delay						
Immediate	13	−4.05	0.70	0.93	.344	0.03
Short delay	15	−3.21	0.53			
Task type						
Spatial requirements with throwing task	7	−3.51	0.75	0.21	.886	0.03
Spatial requirements with adaptation	9	−3.60	0.86			
Spatial requirements without adaptation or throwing	10	−3.70	0.77			
Force production	2	−2.16	1.79			
Feedback modality						
Visual	19	−3.70	0.50	0.58	.452	0.02
Bimodal	9	−2.98	0.81			
Feedback complexity						
Qualitative	8	−5.05	0.85	1.90	.169	0.13[a]
Quantitative and qualitative	18	−3.13	0.49			
Quantitative	3	−3.43	1.44			
Assignment ambiguity						
Low	17	−3.53	0.62	0.18	.834	0.01
Medium	8	−3.71	0.71			
High	3	−2.86	1.34			
Response complexity						
Low	23	−3.45	0.47	0.09	.762	<0.01
High	5	−3.800	1.04			

[a] Medium effect ($\eta_p^2 > 0.06$).

are those errors, which can be corrected on the flight and which are defined as differences between the current bodily states and the desired bodily states. In contrast, high-level errors describe that a desired movement result can no longer be achieved or has already been missed (Krigolson & Holroyd, 2007; Maurer et al., 2021). In common settings of motor learning, augmented feedback refers to high-level errors, while low-level errors are only used for prediction processes (Maurer et al., 2021).

Previous studies also implicated that FRN amplitudes are modulated by the value of the prediction error that is determined by the magnitude of the deviation of feedback valence prediction and the actual outcome, as well as the (motivational) saliency (Kirsch et al., 2022; Sambrook & Goslin, 2015; Stewardson & Sambrook, 2023). We suppose that the utility and importance of a feedback stimulus may be greater in motor tasks than in most categories of cognitive tasks, because feedback information can be used to change subsequent movements immediately in a following trial (e.g., a faster movement execution, an adjustment of a throwing angle, etc.). In contrast, in cognitive tasks, especially in probabilistic learning, only decisions between two elements can be adjusted, based on probabilistic rules that have to be derived and integrated from numerous trials. Consistent with this argumentation, it has been shown that the extent to which individuals can actively influence the outcome of the task increased the FRN amplitude significantly (Bellebaum et al., 2010; Mühlberger et al., 2017; Yeung et al., 2005).

Lastly, it is possible that domain-specific differences could have been induced by P300 effects, a component which overlaps with the FRN. It has been previously shown that execution and selection errors are driven by reward-related differences in both domains (De Bruijn

TABLE 3 Moderator variable analysis of feedback-related negativity latency with weighted descriptive statistics.

	Descriptive statistics			ANOVA		
Moderator variables	***K***	***M* (ms)**	***SD* (ms)**	***F***	***p***	η_p^2
Delay						
Immediate	13	242.47	17.00	1.83	.187	0.07
Short delay	15	271.21	12.73			
Task type						
Spatial requirements with throwing task	7	284.07	17.47	1.04	.393	0.12[a]
Spatial requirements with adaptation	9	258.25	20.17			
Spatial requirements without adaptation or throwing	10	241.03	18.01			
Force production	2	246.17	41.92			
Feedback modality						
Visual	19	273.34	11.42	4.40	.046*	0.15[b]
Bimodal	9	227.31	18.74			
Feedback complexity						
Qualitative	8	272.71	21.89	.23	.795	0.02
Quantitative and qualitative	18	257.53	12.45			
Quantitative	3	273.36	36.76			
Assignment ambiguity						
Low	17	241.63	14.21	1.94	.165	0.13[a]
Medium	8	283.75	16.26			
High	3	267.82	28.21			
Response complexity						
Low	23	267.50	11.21	2.11	.159	0.08[a]
High	5	228.21	24.69			

[a] Medium effect ($\eta_p^2 > 0.06$).
[b] High effect ($\eta_p^2 \geq 0.14$).
*$p < .05$.

et al., 2003; Mushtaq et al., 2022). Additional research with motor tasks and cognitive tasks or a meta-analysis on P300 effects is needed to shed more light on this issue. Furthermore, the domain-specific findings in the present study rely on those tasks, which were included in the previous meta-analysis by Sambrook and Goslin (2015) and the present data set of the meta-analysis. Therefore, group sizes were not equal, which must be considered for data interpretation.

4.2 | Discussion FRN latency

Another difference between motor tasks and cognitive tasks is the integration of a higher amount of internal information in motor tasks (e.g., visual, auditory, proprioceptive, haptic information, as well as efference copies and especially, feedforward control) (Sigrist et al., 2013). This information is used to predict the action's outcome precisely (especially, in later learning stages). In this regard, Maurer et al. (2022) examined that the associated neural correlate of internal feedback processing, as signified by the ERN, increased, while the FRN decreased with learning (Maurer et al., 2022). The average of the number of experimental trials in the meta-analysis ($M = 634.5 \pm 634.67$) was significantly lower than the 4000 trials used by Maurer et al. (2022). Hence, the FRN amplitude was still high and did not diminish significantly within the studies included compared to cognitive tasks. Nevertheless, the internal information is still present and could have been used to accelerate the evaluation process between the predicted and the actual feedback presentation. This might explain the significantly shorter FRN latency observed in motor tasks, as compared to cognitive tasks. The two studies reporting very short FRN latencies suggest that prior sensory information, for example, via visual information about a ball flight curve or tracking position, accelerates the processing of external information (Colino et al., 2017; Maurer et al., 2022). Both studies were examined thoroughly to ensure that the component is really an FRN and not an ERN. Both studies could be integrated into our meta-analysis, since Maurer et al. (2022) and Colino et al. (2017) also published their ERN waveforms as a distinction to the FRN amplitude and argued for both correlates. It must be admitted, however, that a clear line between internal error information and external error information is difficult to draw in many motor learning settings because outcome predictions in motor tasks are always complex and induced by different feedback aspects. Hence, in motor learning, it might be better to allocate the ERN for error information that is predictive of response outcome and mostly used for low-level errors, whereas the FRN component is used for postdictive error processing, where the error cannot be corrected any longer within the same trial (Maurer et al., 2022).

Overall, the FRN latency was examined to be shorter in the motor domain than in the cognitive domain, and some studies deviated from the previous FRN interval of 150–400 ms for pure valence effects presented by Sambrook and Goslin (2015). The large heterogeneity of FRN latencies in motor tasks should be considered when studying the FRN in motor tasks. In addition, experiments should be designed in a way that internal and external feedback processing are clearly differentiated within different time delays.

4.3 | Discussion on moderator variable analysis in the motor domain

As presented in other studies, there are multiple moderator variables that influence the FRN amplitude (e.g., *feedback delay, reward magnitude, reward likelihood, feedback modality, feedback complexity, number of trials*). Therefore, we conducted a moderator variable analysis on the FRN amplitude and the FRN latency. The moderator variable *feedback modality* influenced the FRN latency in the motor domain significantly. Overall, the *feedback modality* plays a major role in motor learning, as movement executions are constantly assessed by integrating visual, auditory, haptic, and proprioceptive information (Sigrist et al., 2013). Already in one of the original papers related to the FRN, Miltner et al. (1997) elucidated the FRN with different modalities of feedback. They revealed that the FRN latency differed as a function of modality. Thereby, auditory feedback induced a shorter FRN latency compared to visual feedback. The same was found in the study of Threadgill et al. (2020), where auditory feedback could be discriminated faster than visual feedback, resulting in a shorter FRN latency. In the present meta-analysis, studies used either visual feedback (e.g., Bediou et al., 2012; Colino et al., 2020; Krause et al., 2020) or bimodal feedback (visual and auditory; e.g., Maurer et al., 2019, 2022; Reuter et al., 2017, 2020). It was found that the FRN latency was shorter after bimodal feedback (when both visual and auditory feedback was given) than after purely visual feedback. Thus, feedback with an (additional) auditory cue results in a shorter FRN latency even when combined with visual feedback. Please note that in some studies using bimodal feedback, auditory feedback was given first to provide qualitative information about a hit or a miss, followed by visual feedback for quantitative information about the precision of a task performance (e.g., Joch et al., 2017; Liu et al. 2021; Maurer et al., 2019, 2022). Therefore, the initial auditory feedback alone may have shortened the FRN latency.

4.4 | Limitations and research desiderata

4.4.1 | Average representation with plotted curves

ERP studies are using grand average curves to illustrate the amplitude, the latency, and the overall timeline of the mean electrode activation of all participants. In meta-analyses, studies are basically used like participants in experiments (Durlak & Lipsey, 1991). The only difference is an additional weighting, where sample sizes are used as multipliers for every study. If the same procedure with grand averages of difference wave curves or conditional curves is used to get a GGA curve of the grand averages of all studies, problems of overlapping may occur, which can lead to a misinterpreted mean FRN amplitude and FRN latency. For example, if the waveform of one study represents a positivity (e.g., a P2) at the same point in time at which another study reports a negativity (e.g., N2), the average of both curves would result in a flat line, even though both studies could have both a P2 and a N2 component. This must be considered when ERP peak analyses are performed. Hence, when conducting an ERP meta-analysis, it must be considered, which analysis procedure will be used and how large the latency heterogeneity of the included studies is. In this regard, it cannot be recommended to calculate and interpret a GGA curve of all studies,

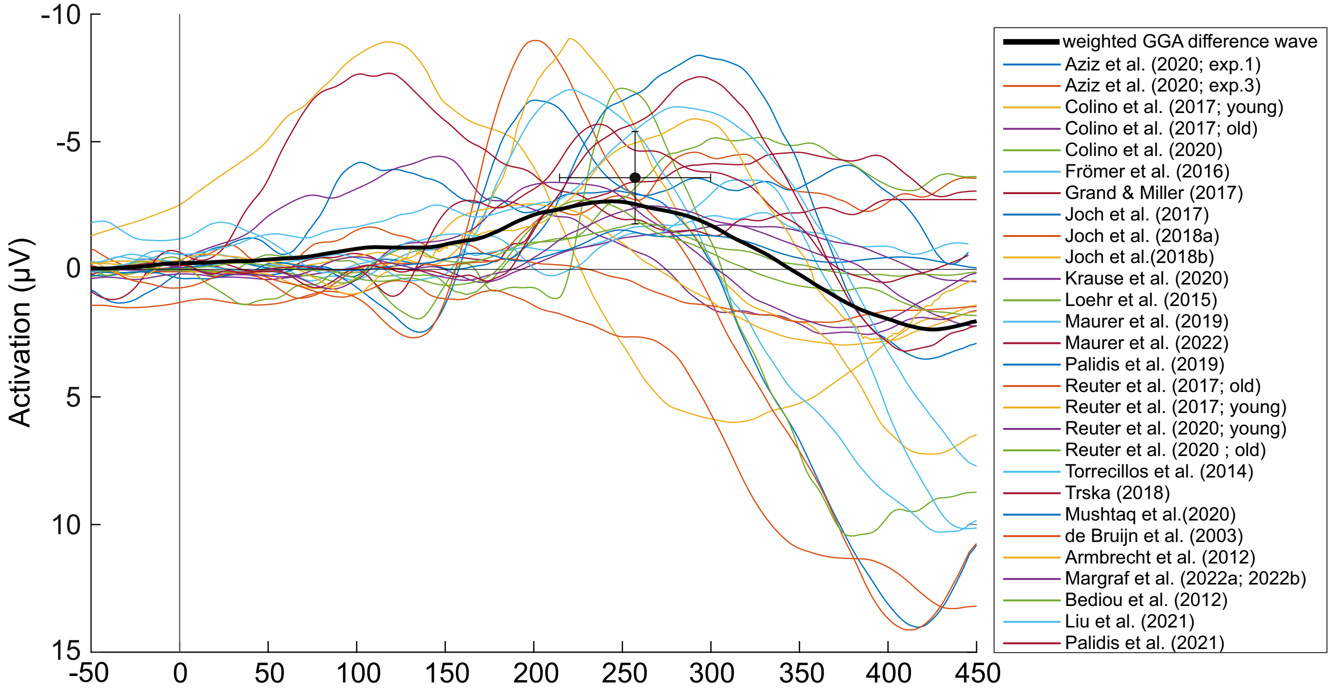

FIGURE 8 Weighted Great Grand Average (GGA) curve of all studies in the motor domain. The colored lines represent the difference waves of the included studies in the motor domain, the black filled line is the calculated weighted GGA curve. The black dot is the calculated weighted feedback-related negativity amplitude and latency of all difference curves as estimated in this meta-analysis.

when having a large heterogeneity of individual studies. Instead, the mean FRN amplitude or the mean FRN latency of each study should be used and weighted for calculating an overall average. For a visualization, the reader may consider Figure 8, which shows the difference in calculating a GGA by averaging all curves or by averaging single effect sizes.

4.4.2 | FRN analysis and differentiation

The way the FRN is analyzed in motor and cognitive studies varies widely. Not only the electrode position differs between FCz, Fz, Cz, and averaged frontal ROIs but also the analysis intervals are different between all studies. In the original articles, the FRN interval is between 200 and 300 ms (Holroyd & Coles, 2002; Miltner et al., 1997), whereas Sambrook and Goslin (2015) advice an interval of 240–340 ms for RPE-FRN and 150–400 ms for valence effects of the FRN. There is also a debate about whether the FRN amplitude should be provided as a difference curve (loss/negative/unfavorable – gain/positive/favorable feedback or gain/positive/favorable – loss/negative/unfavorable feedback) or as a peak measurement of conditional waveforms between previous P2 and N2 (e.g., Krigolson, 2018). Luck (2014) suggested to use the mean amplitude measurement of the difference wave because of the following reasons: (1) if the neural correlate is not interpreted as the FRN but as the RewP, a difference wave can be just inverted to switch from one to the other terminology, (2) a peak analysis gives the risk of a misinterpretation because of different filtering and different task conditions, and (3) the mean analysis avoids relying on outliers. However, recent studies also used both analyses procedures while interpreting FRN$_{diff}$ and FRN$_{peak}$ as different neural correlates (Höltje & Mecklinger, 2020; Peterburs et al., 2016; Weismüller & Bellebaum, 2016). In the present meta-analysis, we decided to use the more robust different waveforms because of the large heterogeneity of tasks and the comparability to the previous meta-analysis of Sambrook and Goslin (2015). For the reader, who is particularly interested in the conditional curves and peak analyses, these can be found in the supplementary materials.

4.4.3 | Limitations of GGA technique

The advantages and disadvantages of GGA technique, which were presented by Sambrook and Goslin (2015), are confirmed. The use of the GGA technique enabled us to digitize data that were already published in a very efficient way without losing data sets. This was especially useful because the data of interest were sometimes missing in the original manuscripts. In this regard, using the GGA technique was very comfortable and efficient to generate identical data sets (same difference wave calculation). Thus, it was possible to align the requested time interval for the analysis of every study. However, close attention must be paid to the exactness of data clicking during the process. Figures of high-ranking journals are often of small size, while the lines plotted are relatively thick to ensure visibility. This makes it even more difficult to generate precise data. To ensure exactness of touchpad-clicked data, waveforms were replotted after construction and thoroughly compared with published waveforms of the original study. To avoid minor inaccuracies in the curves clicked, the curves were additionally smoothed by a moving average of the surrounding five data points. Overall, this secured a high accuracy between clicked and original data.

Another limitation of the GGA technique was the use of simple instead of standardized effect sizes due to a missing opportunity to measure variance in the clicked waveforms. With this limitation, a downweighting of studies with high variance and the overall inclusion of variances of studies were not possible. This has already been mentioned by Sambrook and Goslin (2015).

By using difference waves, deviations between grand average curves were less problematic, which otherwise arise between studies because of different noises of reference electrodes, baseline correction, or filtering between studies (Luck, 2014; Williams et al., 2021). Importantly, Sambrook and Goslin (2015) summarized a high reliability with moderate noise between original and clicked data sets, when calculating a correlation between both data sets ($r = .8$). Accordingly, its usability was supported. In our point of view, the technique is the most suitable for an ERP meta-analysis. However, in further analyses, the resolution and the quality of figures should also be categorized and used as additional weighting factor, besides the study's sample size and automatized image editing programs would be efficient.

5 | CONCLUSION

Augmented feedback is crucial for motor learning, with the FRN being an important neural signature of feedback processing. The FRN has been studied for a long time in the cognitive domain (i.e., for cognitive tasks) and today, a solid body of research exists. This is different for the motor domain (i.e., for motor tasks), where much fewer studies have been published, although the number increased over the last years. Therefore, we were interested in the similarities and differences in neural feedback processing between the motor and cognitive domain. We found a higher FRN amplitude and a shorter FRN latency in the motor domain compared to the cognitive domain. This might be related to the higher complexity of feedback in motor tasks caused by higher degrees of freedom and a higher assignment ambiguity, as well as a higher motivational saliency of motor tasks compared to cognitive tasks. Since bimodal feedback generated a shorter FRN latency compared to visual feedback in motor studies, it can be assumed that using both internal and external sensory error information in motor tasks increases processing speed, probably because of an additional auditory cue. Together, the present meta-analysis provides a comprehensive overview of the similarities and differences in neural feedback processing (as signified by the FRN) between the motor and cognitive domain. This will assist researchers, who are interested to further investigate the neural correlates of feedback processing in motor learning. In this regard, future studies should also examine the influencing factors of the FRN amplitude and the FRN latency in the motor domain in more systematic ways. In doing so, we motivate researchers to use a more consistent analysis procedure for the FRN, as has already been suggested by other authors (Krigolson, 2018; Sambrook & Goslin, 2015; Williams et al., 2021).

AUTHOR CONTRIBUTIONS

Laura Faßbender: Data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – original draft; writing – review and editing. **Daniel Krause:** Conceptualization; project administration; validation; writing – original draft; writing – review and editing. **Matthias Weigelt:** Project administration; supervision; validation; writing – review and editing.

ACKNOWLEDGMENTS

We thank Leonard Gerharz for supporting data analysis and all authors who provided additional evaluation material. Open Access funding enabled and organized by Projekt DEAL.

FUNDING INFORMATION

This work was supported by the Hessisches Ministerium für Wissenschaft und Kunst (HMWK; project “The Adaptive Mind”).

CONFLICT OF INTEREST STATEMENT

We have no known conflict of interest to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the supplementary material of this article.

ORCID

Laura Faßbender https://orcid.org/0000-0001-5654-0143
Daniel Krause https://orcid.org/0000-0001-5391-885X
Matthias Weigelt https://orcid.org/0000-0002-0348-9097

REFERENCES

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. *Journal of Cognitive Neuroscience*, *25*(8), 1249–1260. https://doi.org/10.1162/jocn_a_00385

Arbel, Y., Hong, L., Baker, T. E., & Holroyd, C. B. (2017). It's all about timing: An electrophysiological examination of feedback-based learning with immediate and delayed feedback. *Neuropsychologia*, *99*(3), 179–186. https://doi.org/10.1016/j.neuropsychologia.2017.03.003

Armbrecht, A. S., Gibbons, H., & Stahl, J. (2012). Monitoring force errors: Medial-frontal negativity in a unimanual force-production task. *Psychophysiology*, *49*(1), 56–72. https://doi.org/10.1111/j.1469-8986.2011.01282.x

Aziz, J. R., MacLean, S. J., Krigolson, O. E., & Eskes, G. A. (2020). Visual feedback modulates aftereffects and electrophysiological markers of prism adaptation. *Frontiers in Human Neuroscience*, *14*(138), 1–15. https://doi.org/10.3389/fnhum.2020.00138

Batavia, M., Gianutsos, J. G., Vaccaro, A., & Gold, J. T. (2001). A do-it-yourself membrane-activated auditory feedback device for weight bearing and gait training: A case report. *Archives of Physical Medicine and Rehabilitation*, *82*(4), 541–545. https://doi.org/10.1053/apmr.2001.21931

Bediou, B., Koban, L., Rosset, S., Pourtois, G., & Sander, D. (2012). Delayed monitoring of accuracy errors compared to commission errors in ACC. *NeuroImage*, *60*(4), 1925–1936. https://doi.org/10.1016/j.neuroimage.2012.02.010

Bellebaum, C., & Daum, I. (2008). Learning-related changes in reward expectancy are reflected in the feedback-related negativity. *European Journal of Neuroscience*, *27*(7), 1823–1835. https://doi.org/10.1111/j.1460-9568.2008.06138.x

Bellebaum, C., Kobza, S., Thiele, S., & Daum, I. (2010). It was not my fault: Event-related brain potentials in active and observational learning from feedback. *Cerebral Cortex*, *20*(12), 2874–2883. https://doi.org/10.1093/cercor/bhq038

Bernstein, N. A. (1967). *The coordination and regulation of movements*. Pergamon Press.

Bismark, A. W., Hajcak, G., Whitworth, N. M., & Allen, J. J. (2013). The role of outcome expectations in the generation of the feedback-related negativity. *Psychophysiology*, *50*(2), 125–133. https://doi.org/10.1111/j.1469-8986.2012.01490.x

Caligiore, D., Arbib, M. A., Miall, R. C., & Baldassarre, G. (2019). The super-learning hypothesis: Integrating learning processes across cortex, cerebellum and basal ganglia. *Neuroscience and Biobehavioral Reviews*, *100*, 19–34. https://doi.org/10.1016/j.neubiorev.2019.02.008

Chang, Y., Phillips, M. R., Guymer, R. H., Thabane, L., Bhandari, M., Chaudhary, V., & RETINA Study Group. (2022). The 5 min meta-analysis: Understanding how to read and interpret a forest plot. *Eye*, *36*(4), 673–675. https://doi.org/10.1038/s41433-021-01867-6

Chein, J. M., & Schneider, W. (2012). The brain's learning and control architecture. *Current Directions in Psychological Science*, *21*(2), 78–84. https://doi.org/10.1177/0963721411434977

Cockburn, J., & Holroyd, C. B. (2018). Feedback information and the reward positivity. *International Journal of Psychophysiology*, *132*, 243–251. https://doi.org/10.1016/j.ijpsycho.2017.11.017

Colino, F. L., Heath, M., Hassall, C. D., & Krigolson, O. E. (2020). Electroencephalographic evidence for a reinforcement learning advantage during motor skill acquisition. *Biological Psychology*, *151*, 107849. https://doi.org/10.1016/j.biopsycho.2020.107849

Colino, F. L., Howse, H., Norton, A., Trska, R., Pluta, A., Luehr, S. J. C., Handy, T. X., & Krigolson, O. E. (2017). Older adults display diminished error processing and response in a continuous tracking task. *Psychophysiology*, *54*(11), 1706–1713. https://doi.org/10.1111/psyp.12907

De Bruijn, E. R. A., Hulstijn, W., Meulenbroek, R. G. J., & Van Galen, G. P. (2003). Action monitoring in motor control: ERPs following selection and execution errors in a force production task. *Psychophysiology*, *40*(5), 786–795. https://doi.org/10.1111/14698986.00079

Debas, K., Carrier, J., Orban, P., Barakat, M., Lungu, O., Vandewalle, G., Hadj Tahar, A., Bellec, P., Karni, A., Ungerleider, L. G., Benali, H., & Doyon, J. (2010). Brain plasticity related to the consolidation of motor sequence learning and motor adaptation. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(41), 17839–17844. https://doi.org/10.1073/pnas.1013176107

Doyon, J., Penhune, V., & Ungerleider, L. G. (2003). Distinct contribution of the cortico-striatal and cortico-cerebellar systems to motor skill learning. *Neuropsychologia*, *41*(3), 252–262. https://doi.org/10.1016/S0028-3932(02)00158-6

Durlak, J. A., & Lipsey, M. W. (1991). A practitioner's guide to meta-analysis. *American Journal of Community Psychology*, *19*(3), 291–332. https://doi.org/10.1007/bf00938026

Ferdinand, N. K., Mecklinger, A., Kray, J., & Gehring, W. J. (2012). The processing of unexpected positive response outcomes in the mediofrontal cortex. *Journal of Neuroscience*, *32*(35), 12087–12092. https://doi.org/10.1523/JNEUROSCI.141012.2012

Fitts, P. M., & Posner, M. I. (1967). *Human performance*. Brooks/Cole.

Foerde, K., & Shohamy, D. (2011). Feedback timing modulates brain systems for learning in humans. *Journal of Neuroscience*, *31*(37), 13157–13167. https://doi.org/10.1523/JNEUROSCI.2701-11.2011

Frömer, R., Stürmer, B., & Sommer, W. (2016). The better, the bigger: The effect of graded positive performance feedback on the reward positivity. *Biological Psychology*, *114*, 61–68. https://doi.org/10.1016/j.biopsycho.2015.12.011

Fu, W. T., & Anderson, J. R. (2008). Solving the credit assignment problem: Explicit and implicit learning in action sequences with probabilistic outcomes. *Psychological Research*, *72*, 321–330. https://doi.org/10.1007/s00426-007-0113-7

Gehring, W. J., & Willoughby, A. R. (2002). The medial frontal cortex and the rapid processing of monetary gains and losses. *Science*, *295*, 2279–2282. https://doi.org/10.1126/science.1066893

Gibbons, H., Schnuerch, R., & Stahl, J. (2016). From positivity to negativity bias: Ambiguity affects the neurophysiological signatures of feedback processing. *Journal of Cognitive Neuroscience*, *28*(4), 542–557. https://doi.org/10.1162/jocn_a_00921

Glimcher, P. W. (2011). Understanding dopamine and reinforcement learning: The dopamine reward prediction error hypothesis. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(42), 15647–15654. https://doi.org/10.1073/pnas.1115170108

Grand, K. F., Daou, M., Lohse, K. R., & Miller, M. W. (2017). Investigating the mechanisms underlying the effects of an incidental choice on motor learning. *Journal of Motor Learning and Development*, *5*(2), 207–226. https://doi.org/10.1123/jmld.2016-0041

Höltje, G., & Mecklinger, A. (2020). Feedback timing modulates interactions between feedback processing and memory encoding: Evidence from event-related potentials. *Cognitive, Affective, & Behavioral Neuroscience*, *20*(2), 250–264. https://doi.org/10.3758/s13415-019-00765-5

Hajcak, G., Moser, J. S., Holroyd, C. B., & Simons, R. F. (2007). It's worse than you thought: The feedback negativity and violations of reward prediction in gambling tasks. *Psychophysiology*, *44*(6), 905–912. https://doi.org/10.1111/j.1469-8986.2007.00567.x

Hinneberg, B. M., & Hegele, M. (2021). Acting in temporal contexts: On the behavioral and neurophysiological consequences of feedback delays. *Neuroscience*, *486*, 91–102. https://doi.org/10.1016/j.neuroscience.2021.06.028

Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, *109*(4), 679–709. https://doi.org/10.1037/0033-295X.109.4.679

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Sage.

Joch, M., Hegele, M., Maurer, H., Müller, H., & Maurer, L. K. (2017). Brain negativity as an indicator of predictive error processing: The contribution of visual action effect monitoring. *Journal of Neurophysiology*, *118*(1), 486–495. https://doi.org/10.1152/jn.00036.2017

Joch, M., Hegele, M., Maurer, H., Müller, H., & Maurer, L. K. (2018a). Online movement monitoring modulates feedback processing in motor learning: An analysis of event-related potentials. *Journal of Motor Learning and Development*, *6*(S1), S138–S153. https://doi.org/10.1123/jmld.2016-0075

Joch, M., Hegele, M., Maurer, H., Müller, H., & Maurer, L. K. (2018b). Accuracy of motor error predictions for different sensory signals. *Frontiers in Psychology*, *9*, 1376. https://doi.org/10.3389/fpsyg.2018.01376

Künzell, S. (2023). Aktuelle Motoriktheorien. In A. Güllich & M. Krüger (Eds.), *Bewegung, Training, Leistung und Gesundheit* (Vol. 1, pp. 187–203). Springer. https://doi.org/10.1007/978-3-662-53386-4_56-1

Kirsch, F., Kirschner, H., Fischer, A. G., Klein, T. A., & Ullsperger, M. (2022). Disentangling performance-monitoring signals encoded in feedback-related EEG dynamics. *NeuroImage*, *257*, 119322. https://doi.org/10.1016/j.neuroimage.2022.119322

Krause, D., Koers, T., & Maurer, L. K. (2020). Valence-dependent brain potentials of processing augmented feedback in learning a complex arm movement sequence. *Psychophysiology*, *57*(3), e13508. https://doi.org/10.1111/psyp.13508

Krigolson, O. E. (2018). Event-related brain potentials and the study of reward processing: Methodological considerations. *International Journal of Psychophysiology*, *132*, 175–183. https://doi.org/10.1016/j.ijpsycho.2017.11.007

Krigolson, O. E., Heinekey, H., Kent, C. M., & Handy, T. C. (2012). Cognitive load impacts error evaluation within medial-frontal cortex. *Brain Research*, *1430*, 62–67. https://doi.org/10.1016/j.brainres.2011.10.028

Krigolson, O. E., & Holroyd, C. B. (2007). Hierarchical error processing: different errors, different systems. *Brain research*, *1155*, 70–80. https://doi.org/10.1016/j.brainres.2007.04.024

Lange, S., Leue, A., & Beauducel, A. (2012). Behavioral approach and reward processing: Results on feedback-related negativity and P3 component. *Biological Psychology*, *89*(2), 416–425. https://doi.org/10.1016/j.biopsycho.2011.12.004

Levy, W. B., & Sederberg, P. B. (1997). A neural network model of hippocampally mediated trace conditioning. In *Proceedings of International Conference on Neural Networks (ICNN'97)* (Vol. 1, pp. 372–376). https://doi.org/10.1109/ICNN.1997.611696.

Liu, H., Ting-Ju Chiang, J., Fehr, R., Xu, M., & Wang, S. (2017). How do leaders react when treated unfairly? Leader narcissism and self-interested behavior in response to unfair treatment. *Journal of Applied Psychology*, *102*(11), 1590–1599. https://doi.org/10.1037/apl0000237

Liu, Y., & Gehring, W. J. (2009). Loss feedback negativity elicited by single-versus conjoined-feature stimuli. *Neuroreport*, *20*(6), 632–636. https://doi.org/10.1097/WNR.0b013e32832a3250

Liu, S., Clements, J. M., Kirsch, E. P., Rao, H. M., Zielinski, D. J., Lu, Y., Mainsah, B. O., Potter, N. D., Sommer, M. A., Kopper, R., & Appelbaum, L. G. (2021). Psychophysiological markers of performance and learning during simulated marksmanship in immersive virtual reality. *Journal of Cognitive Neuroscience*, *33*(7), 1253–1270. https://doi.org/10.1162/jocn_a_01713

Loehr, J. D., Kourtis, D., & Brazil, I. A. (2015). It's not just my fault: Neural correlates of feedback processing in solo and joint action. *Biological Psychology*, *111*, 1–7. https://doi.org/10.1016/j.biopsycho.2015.08.004

Luck, S. J. (2014). *An introduction to the event-related potential technique* (2nd ed.). MIT Press.

Mühlberger, C., Angus, D. J., Jonas, E., Harmon-Jones, C., & Harmon-Jones, E. (2017). Perceived control increases the reward positivity and stimulus preceding negativity. *Psychophysiology*, *54*(2), 310–322. https://doi.org/10.1111/psyp.12786

Margraf, L., Krause, D., & Weigelt, M. (2022a). 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. (2022b). 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

Mars, R. B., De Bruijn, E. R. A., Hulstijn, W., Miltner, W. H. R., & Coles, M. G. H. (2004). What if I told you: "You were wrong"? Brain potentials and behavioral adjustments elicited by feedback in a time-estimation task. In M. Ullsperger & M. Falkenstein (Eds.), *Errors, conflict, and the brain. Current opinions on performance* *monitoring* (pp. 129–134). MPI of Cognitive Neuroscience. http://discovery.ucl.ac.uk/182655/

Maurer, L. K., Joch, M., Hegele, M., Maurer, H., & Müller, H. (2019). Predictive error processing distinguishes between relevant and irrelevant errors after visuomotor learning. *Journal of Vision*, *19*(4), 1–13. https://doi.org/10.1167/19.4.18

Maurer, L. K., Joch, M., Hegele, M., Maurer, H., & Müller, H. (2022). Relevance of predictive and postdictive error information in the course of motor learning. *Neuroscience*, *486*, 77–90. https://doi.org/10.1016/j.neuroscience.2021.05.007

Maurer, L. K., Joch, M., Hegele, M., & Müller, H. (2021). Focused review on neural correlates of different types of motor errors and related terminological issues. *Journal of Human Kinetics*, *76*(1), 67–81. https://doi.org/10.2478/hukin-2020-0087

Miltner, W. H. R., Braun, C. H., & Coles, M. G. H. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: Evidence for a "generic" neural system for error detection. *Journal of Cognitive Neuroscience*, *9*(6), 788–798. https://doi.org/10.1162/jocn.1997.9.6.788

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7), 1–6. https://doi.org/10.1371/journal.pmed.1000097

Mushtaq, F., McDougle, S. D., Craddock, M. P., Parvin, D. E., Brookes, J., Schaefer, A., Mon-Williams, M., Taylor, J. A., & Ivry, R. B. (2022). Distinct neural signatures of outcome monitoring after selection and execution errors. *Journal of Cognitive Neuroscience*, *34*(5), 748–765. https://doi.org/10.1101/853317

Nieuwenhuis, S., Ridderinkhof, K. R., Talsma, D., Coles, M. G. H., Holroyd, C. B., Kok, A., & Van Der Molen, M. W. (2002). A computational account of altered error processing in older age: Dopamine and the error-related negativity. *Cognitive, Affective, & Behavioral Neuroscience*, *2*(1), 19–36. https://doi.org/10.3758/CABN.2.1.19

Nikooyan, A. A., & Ahmed, A. A. (2015). Reward feedback accelerates motor learning. *Journal of Neurophysiology*, *113*(2), 633–646. https://doi.org/10.1152/jn.00032.2014

Palidis, D. J., Cashaback, J. G. A., & Gribble, P. L. (2019). Neural signatures of reward and sensory error feedback processing in motor learning. *Journal of Neurophysiology*, *121*(4), 1561–1574. https://doi.org/10.1152/jn.00792.2018

Palidis, D. J., McGregor, H. R., Vo, A., MacDonald, P. A., & Gribble, P. L. (2021). Null effects of levodopa on reward-and error-based motor adaptation, savings, and anterograde interference. *Journal of Neurophysiology*, *126*(1), 47–67. https://doi.org/10.1152/jn.00696.2020

Paul, K., Vassena, E., Severo, M. C., & Pourtois, G. (2020). Dissociable effects of reward magnitude on fronto-medial theta and FRN during performance monitoring. *Psychophysiology*, *57*(2), 1–17. https://doi.org/10.1111/psyp.13481

Peterburs, J., Kobza, S., & Bellebaum, C. (2016). Feedback delay gradually affects amplitude and valence specificity of the feedback-related negativity (FRN). *Psychophysiology*, *53*(2), 209–215. https://doi.org/10.1111/psyp.12560

Petrofsky, J. (2001). The use of electromyogram biofeedback to reduce Trendelenburg gait. *European Journal of Applied Physiology*, *85*(5), 491–495. https://doi.org/10.1007/s004210100466

Pfabigan, D. M., Gittenberger, M., & Lamm, C. (2019). Social dimension and complexity differentially influence brain responses during feedback processing. *Social Neuroscience*, *14*(1), 26–40. https://doi.org/10.1080/17470919.2017.1395765

Pfabigan, D. M., Sailer, U., & Lamm, C. (2015). Size does matter! Perceptual stimulus properties affect event-related potentials during feedback processing. *Psychophysiology*, *52*(9), 1238–1247. https://doi.org/10.1111/psyp.12458

Proudfit, G. H. (2015). The reward positivity: From basic research on reward to a biomarker for depression. *Psychophysiology*, *52*(4), 449–459. https://doi.org/10.1111/psyp.12370

Reuter, E. M., Leow, L. A., & Carroll, T. J. (2020). Task feedback processing differs between young and older adults in visuomotor rotation learning despite similar initial adaptation and savings. *Neuroscience*, *451*, 79–98. https://doi.org/10.1016/j.neuroscience.2020.09.038

Reuter, E. M., Pearcey, G. E. P., & Carroll, T. J. (2017). Greater neural responses to trajectory errors are associated with superior force field adaptation in older adults. *Experimental Gerontology*, *110*, 105–117. https://doi.org/10.1016/j.exger.2018.05.020

Rothkopf, C. A., & Ballard, D. H. (2010). Credit assignment in multiple goal embodied visuomotor behavior. *Frontiers in Psychology*, *1*, 173. https://doi.org/10.3389/fpsyg.2010.00173

Ruffaldi, E., Filippeschi, A., Frisoli, A., Sandoval, O., Avizzano, C. A., & Bergamasco, M. (2009). Vibrotactile perception assessment for a rowing training system. *IEEE*, *3*, 350–355. https://doi.org/10.1109/WHC.2009.4810849

Sambrook, T. D., & Goslin, J. (2015). A neural reward prediction error revealed by a meta-analysis of ERPs using great grand averages. *Psychological Bulletin*, *141*(1), 213–235. https://doi.org/10.1037/bul0000006

San Martín, R. (2012). Event-related potential studies of outcome processing and feedback-guided learning. *Frontiers in Human Neuroscience*, *6*, 304. https://doi.org/10.3389/fnhum.2012.00304

Sato, A., Yasuda, A., Ohira, H., Miyawaki, K., Nishikawa, M., Kumano, H., & Kuboki, T. (2005). Effects of value and reward magnitude on feedback negativity and P300. *Neuroreport*, *16*(4), 407–411. https://doi.org/10.1097/00001756-200503150-00020

Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron*, *36*(2), 241–263. https://doi.org/10.1016/S0896-6273(02)00967-4

Seidler, R. D., Kwak, Y., Fling, B. W., & Bernard, J. A. (2013). Neurocognitive mechanisms of error-based motor learning. *Progress in Motor Control*, *782*, 39–60. https://doi.org/10.1007/978-1-4614-5465-6

Shi, L., & Lin, L. (2019). The trim-and-fill method for publication bias: Practical guidelines and recommendations based on a large database of meta-analyses. *Medicine*, *98*(23), e15987. https://doi.org/10.1097/MD.0000000000015987

Sigrist, R., Rauter, G., Riener, R., & Wolf, P. (2013). Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review. *Psychonomic Bulletin and Review*, *20*(1), 21–53. https://doi.org/10.3758/s13423-012-0333-8

Sterne, J. A., Sutton, A. J., Ioannidis, J. P., Terrin, N., Jones, D. R., Lau, J., Carpenter, J., Rücker, G., Harbord, R. M., Schmid, C. H., Tetzlaff, J., Deeks, J. J., Peters, J., Macaskill, P., Schwarzer, G., Duval, S., Altman, D. G., Moher, D., & Higgins, J. P. (2011). Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ*, *343*, d4002. https://doi.org/10.1136/bmj.d4002

Stewardson, H., & Sambrook, T. D. (2023). Valence precedes value in neural encoding of prediction error. *Psychophysiology*, *60*(7), e14266. https://doi.org/10.1111/psyp.14266

Sun, M., Ren, X., & Cao, X. (2011). Effects of multimodal error feedback on human performance in steering tasks. *Information and Media Technologies*, *6*(1), 193–201. https://doi.org/10.11185/imt.6.193

Threadgill, A. H., Ryan, J., Jordan, C., & Hajcak, G. (2020). The reward positivity: Comparing visual and auditory feedback. *Biological Psychology*, *154*, 107907. https://doi.org/10.1016/j.biopsycho.2020.107907

Torrecillos, F., Albouy, P., Brochier, T., & Malfait, N. (2014). Does the processing of sensory and reward-prediction errors involve common neural resources? Evidence from a frontocentral negative potential modulated by movement execution errors. *Journal of Neuroscience*, *34*(14), 4845–4856. https://doi.org/10.1523/JNEUROSCI.4390-13.2014

Trska, R. (2018). *Motor expectancy: The modulation of the reward positivity in a reinforcement learning motor task* [Unpublished master thesis]. University of Victoria.

Van Erp, J. B., & Van Veen, H. A. (2004). Vibrotactile in-vehicle navigation system. *Transportation Research Part F: Traffic Psychology and Behaviour*, *7*(4–5), 247–256. https://doi.org/10.1016/j.trf.2004.09.003

Verhagen, A. P., & Ferreira, M. L. (2014). Forest plots. *Journal of Physiotherapy*, *60*(3), 170–173. https://doi.org/10.1016/j.jphys.2014.06.021

Wallenstein, G. V., Hasselmo, M. E., & Eichenbaum, H. (1998). The hippocampus as an associator of discontiguous events. *Trends in Neurosciences*, *21*(8), 317–323. https://doi.org/10.1016/s0166-2236(97)01220-4

Walsh, M. M., & Anderson, J. R. (2012). Learning from experience: Event-related potential correlates of reward processing, neural adaptation, and behavioral choice. *Neuroscience & Biobehavioral Reviews*, *36*(8), 1870–1884. https://doi.org/10.1016/j.neubiorev.2012.05.008

Weinberg, A., Luhmann, C. C., Bress, J. N., & Hajcak, G. (2012). Better late than never? The effect of feedback delay on ERP indices of reward processing. *Cognitive, Affective, & Behavioral Neuroscience*, *12*(4), 671–677. https://doi.org/10.3758/s13415-012-0104-z

Weismüller, B., & Bellebaum, C. (2016). Expectancy affects the feedback-related negativity (FRN) for delayed feedback in probabilistic learning. *Psychophysiology*, *53*(11), 1739–1750. https://doi.org/10.1111/psyp.12738

Williams, C. C., Ferguson, T. D., Hassall, C. D., Abimbola, W., & Krigolson, O. E. (2021). The ERP, frequency, and time–frequency correlates of feedback processing: Insights from a large sample study. *Psychophysiology*, *58*(2), e13722. https://doi.org/10.1111/psyp.13722

Winstein, C. J., Pohl, P. S., & Lewthwaite, R. (1994). Effects of physical guidance and knowledge of results on motor learning: Support for the guidance hypothesis. *Research quarterly for exercise and sport*, *65*(4), 316–323. https://doi.org/10.1080/02701367.1994.10607635

Wolpert, D. M., & Kawato, M. (1998). Multiple paired forward and inverse models for motor control. *Neural Networks*, *11*(7–8), 1317–1329. https://doi.org/10.1016/S08936080(98)00066-5

Yeung, N., Holroyd, C. B., & Cohen, J. D. (2005). ERP correlates of feedback and reward processing in the presence and absence of response choice. *Cerebral Cortex*, *15*(5), 535–544. https://doi.org/10.1093/cercor/bhh153

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Data S1: Supporting Information

Data S2: Supporting Information

How to cite this article: Faßbender, L., Krause, D., & Weigelt, M. (2023). Feedback processing in cognitive and motor tasks: A meta-analysis on the feedback-related negativity. *Psychophysiology*, *60*, e14439. https://doi.org/10.1111/psyp.14439