Two perspectives on response monitoring:

Perfectionism-related variations and post-response adaptation

Inauguraldissertation

zur

Erlangung des Doktorgrades

der Humanwissenschaftlichen Fakultät

der Universität zu Köln

nach der Promotionsordnung vom 18.12.2018

vorgelegt von

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aus [redacted]

März 2023

Diese Dissertation wurde von der Humanwissenschaftlichen Fakultät der Universität zu Köln im Juli 2023 angenommen.

Abstract

The cognitive system needs to monitor actions to ensure that the intended actions are successfully executed and to intervene when deviations from the intended actions are detected. In two studies, we investigated systematic variations of response monitoring *between* (Study 1) and *within* (Study 2) individuals. We assessed response monitoring using electrophysiological markers. The error/correct negativity (Ne/c) and the error/correct positivity (Pe/c) are both components of the event-related potential that occur within 300 ms after a motor response. Usually, they have higher peak amplitudes following errors compared to correct responses. In Study 1, we related these indicators of response monitoring to two dimensions of perfectionism and found that individuals who strive for flawlessness purely because they are afraid of being evaluated negatively by others (evaluative concern perfectionists) displayed less error-specific early response monitoring (indicated by the Ne/c) than non-perfectionists and individuals who set themselves high goals and are internally motivated to perform flawlessly (personal standards perfectionists). In Study 2, we linked the single-trial peak estimates of the Ne/c and Pe/c amplitudes to indicators of post-response adaptation derived by a diffusion model decomposition of post-response times and accuracies. We found that early response monitoring reflected by the Ne/c was associated with a higher decision threshold and a greater focus on task-relevant features on the subsequent trial. The Pe/c, on the other hand, was associated with a lower decision threshold when speed was relevant. The interplay of Ne/c- and Pe/c-related processes may thus ensure that subsequent responses are as fast and as accurate as possible by adjusting the decision threshold. The thesis points out how future research could benefit from integrating both levels of response monitoring by investigating how individual differences as described in Study 1 modulate basic post-response adaptation mechanisms as delineated in Study 2.

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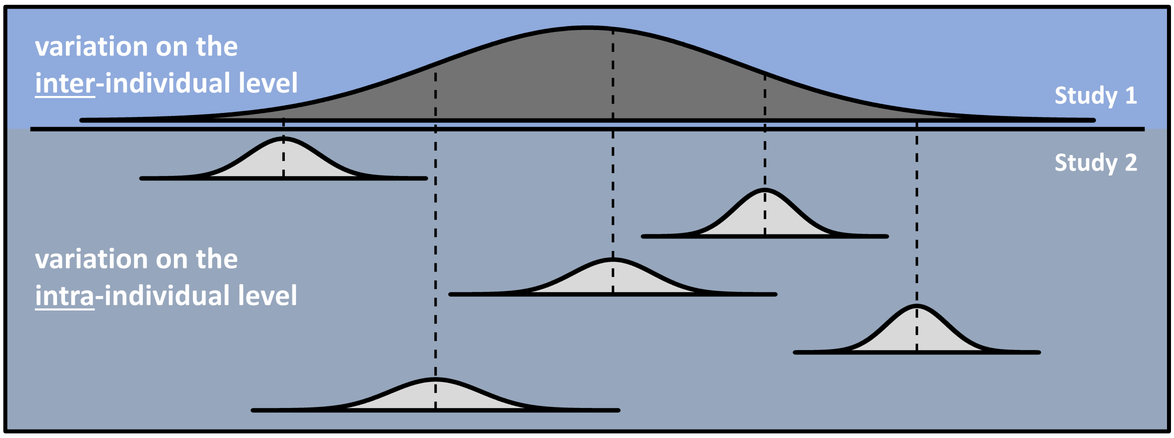
1 Introduction

Picture a harried PhD student sitting in front of his laptop, diligently writing his dissertation, a cup of coffee right next to the laptop. As he reaches for his phone to engage in some short-term procrastination, his hand grazes the cup. The cup begins to tilt, but just before the coffee pours over the desk and probably the laptop, destroying all the progress of the last couple of hours or even days, the PhD student manages to grab the cup and just barely avoids disaster. Within just a few hundred milliseconds, the student's response monitoring system seems to have detected an undesired action outcome and to have initiated processes aimed at preventing the undesired outcome. While this PhD student's cognitive system saved him from losing days of progress, another person's cognitive system may not have successfully contributed to preventing the undesired action outcome. People differ in their ability to monitor their responses and this variability in response monitoring has been the subject of a large body of research. Furthermore, just like there is variability in response monitoring between different people, there is also variability of response monitoring within the same person. Had the situation described above occurred at the end of a long and exhausting day, the PhD student might not have been able to grab the cup and prevent the coffee from spilling. In the current thesis, both levels of response monitoring – i.e. the inter-individual and the intra-individual level – will be elucidated.

From a more scientific point of view, response monitoring refers to the process of comparing expected action outcomes to actual action outcomes and detecting potential discrepancies (Alexander & Brown, 2010). As the examples from everyday life demonstrate, it can be studied on (at least) two different levels (Figure 1). On a higher level, researchers may investigate how individuals differ in how they monitor their responses. In this line of research, the primary unit of investigation are individuals. Research questions are for example "How is response monitoring in people with an obsessive compulsive disorder

Figure 1

Two levels of response monitoring



Note. The distribution on the higher (inter-individual) level indicates variability *between* individuals. The distributions on the lower (intra-individual) level represent variability *within* these individuals.

different from that in healthy people?" (e.g. Endrass & Ullsperger, 2014; Gehring et al., 2000; Riesel, 2019) or "How are the Big Five personality traits related to response monitoring?" (e.g. Imhof & Rüsseler, 2019; Pailing & Segalowitz, 2004; Suzuki et al., 2020). On a lower level, researchers may zoom in on one particular individual and investigate response monitoring on single trials and how response monitoring is modulated by variables that also vary from trial to trial. To study response monitoring on the single-trial level, indicators of response monitoring need to be obtained for every trial. Potential research questions are for example "To what degree do different indicators of response monitoring like the error negativity and the error positivity correlate with each other?" (e.g. Hughes & Yeung, 2011; Steinhauser & Yeung, 2010) or "How does response monitoring on one trial impact sensory processing on the following trial?" (e.g. Beatty et al., 2018; Buzzell et al., 2017).

In my dissertation, I studied response monitoring on both levels. In the first study (Mattes et al., 2023), we investigated how response monitoring is related to perfectionism (higher level), a personality trait that is characterised by the striving for flawlessness. Response monitoring plays a central role in the achievement of flawless performance, hence understanding how response monitoring is associated with perfectionism may help to understand the neuronal underpinnings of this personality trait in particular. In the second study (Mattes et al., 2022)[1], we examined the link between response monitoring on trial *n*, and behavioural and cognitive adaptation on the subsequent trial, i.e. trial *n* + 1 (lower level). Although it is widely assumed that effective response monitoring positively impacts performance on the subsequent trial, the exact mechanism remains unclear. Our study addresses this issue by proposing specific mechanisms that link response monitoring and post-response adaptation. In both studies, we employed and combined a broad range of methods, and we advanced existing methods to leverage and extend the insights we can gain from the data (Figure 2).

In the following, I will first elaborate on the concept of response monitoring in more detail and present two electrophysiological indicators of response monitoring (chapter 2). Then, I will briefly introduce the most important aspects of perfectionism (chapter 3) and post-response adaptation (chapter 4), summarise the two studies and discuss the conceptual and methodological contribution these two studies made to the respective field and the respective level of response monitoring. I will end with concluding remarks including limitations of the current studies and future directions (chapter 5).

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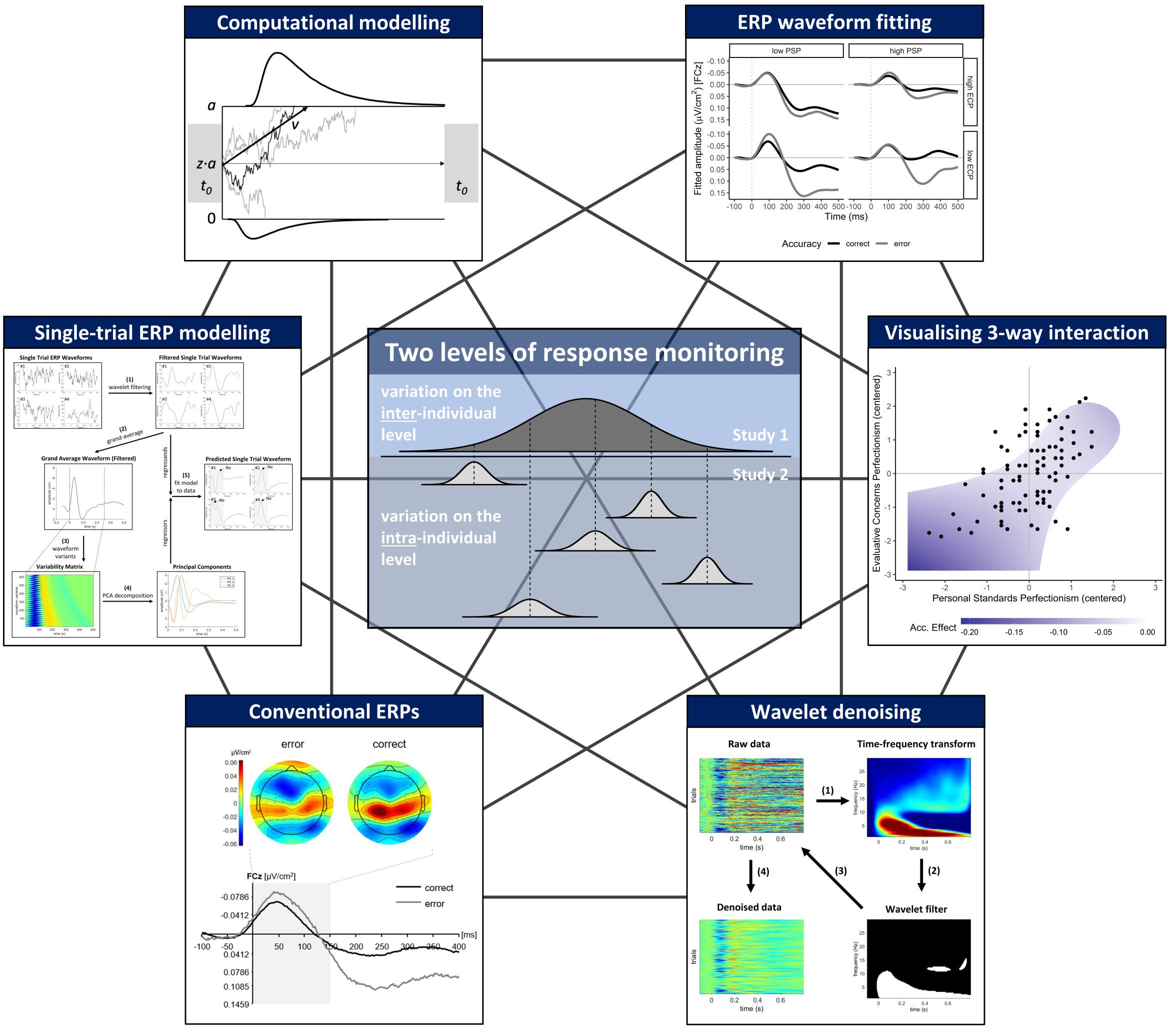
[1] Note that Study 2 was published prior to Study 1. However, in this thesis, the studies are not presented in chronological order, but in “conceptual” order, starting on the upper level of response monitoring and then zooming in on the lower level of response monitoring.

Figure 2

Methodological diversity and integration



Note. Exemplary illustration of the methods that were employed, combined and developed in the context of the current studies to investigate the two levels of response monitoring represented in the centre. A detailed description and depiction of the methods is provided in the published studies – where necessary – additionally in the current thesis. (Please note that the connections between the individual methods are symbolic and do not necessarily indicate that all methods were combined simultaneously.)

2 Response monitoring

Response monitoring is one of the cognitive processes that jointly form the executive functions (Henderson et al., 2006). It refers to an agent's ability to monitor action outcomes, compare them to intended outcomes, and potentially detect deviations from the intended outcomes (Schaaf et al., 2022). Response monitoring is an important prerequisite for goal-directed behaviour (Henderson et al., 2006). In the short term, it allows agents to immediately correct their actions (Beatty et al., 2021; Navarro-Cebrian et al., 2016); in the long term, it allows them to optimize their behaviour (Ullsperger et al., 2014; Wessel, 2018).

Response monitoring is often assessed using the electroencephalography (EEG), a non-invasive neuroimaging technique that allows to record an electric field on the scalp. This field is generated by postsynaptic dendritic potentials of synchronously active populations of pyramidal neurons (Britton et al., 2016; Ward, 2015, Chapter 3). The EEG has a series of benefits that have made it one of the most popular methods in the research of response monitoring. First, it is a non-invasive and non-stimulating technique, i.e. it is safe for participants and comparatively easy to conduct (Luck, 2014, Chapter 1). Second, it provides continuous data and thus enables researchers to selectively investigate dissociable processing stages that are all subsumed in point-measures like response times (Luck, 2014, Chapter 1). Third and most importantly, the EEG has a very high temporal resolution. Cognitive and associated neural processes often unfold within milliseconds. The EEG's high temporal resolution allows to track changes in these processes with hardly any delay (Beres, 2017; Luck, 2014, Chapter 1). These properties make the EEG a highly suitable neuroscientific method to study response monitoring.

Two common markers of response monitoring derived from the EEG recording are the error negativity and the error positivity, two components of the event-related potential

(ERP). In the following, both components and their functional significance will be described in more detail.

2.1 The error negativity

The *error negativity* (Ne, Falkenstein et al., 1991; also termed *error-related negativity* or ERN, Gehring et al., 1993) is a component of the event-related potential with a medial-fronto-central scalp distribution and a negative peak at around 100 ms following incorrect responses (Gehring et al., 2012). Its postulated neural generator is the anterior cingulate cortex (ACC; Ridderinkhof et al., 2004). Following correct responses, a smaller negative deflection may be observed, termed the correct negativity (Nc; Vidal et al., 2000). In this thesis, I will abbreviate both components jointly as the Ne/c and specify – when necessary – whether I refer to the Ne/c following errors or correct responses. Although this may seem more of a terminological remark, it also emphasises that the Ne and Nc reflect similar processes (Vidal et al., 2003), have similar topographies (Hoffmann & Falkenstein, 2010; Vidal et al., 2000), and share the ACC as a neural generator (Roger et al., 2010).

Early research on the Ne/c suggested that it reflects the detection of an error, i.e. the detection of a potential mismatch between the intended action outcome and the actual outcome (*error detection theory*; Coles et al., 2001; Falkenstein et al., 1991). The intended outcome is assumed to be internally represented as the outcome of the response selection process while the actual outcome is represented by the efference copy of the motor movement (Falkenstein et al., 1991; Gehring et al., 1993). In this context, the Ne/c indicates the process or result of comparing these two representations with each other. However, the error detection account assumes the existence of a mental representation of the correct response (Coles et al., 2001) that may, for example, emerge from continued stimulus processing even after a response has already been initiated (Yeung & Summerfield, 2012). *The conflict monitoring theory* of the Ne/c circumvents this assumption by postulating that the Ne/c reflects response conflict (rather than error detection) caused by the simultaneous activation of multiple competing response alternatives (Botvinick et al., 2001). This account of the Ne/c draws on studies of the ACC – the postulated neural generator of the Ne/c – that show that ACC activation is associated with response conflict and that trials on which a response conflict occurs are more likely to produce errors than trials without response conflict (Yeung et al., 2004). A third account – the *reinforcement learning theory* – proposes that the Ne/c is the result of a learning signal generated in the basal ganglia and projected via the mesencephalic dopamine system to the ACC. The ACC may then trigger further processes that aim at improving performance in the current task. (Holroyd et al., 2005; Holroyd & Coles, 2002). The reinforcement learning theory thus focusses more on the input the ACC receives from other brain areas than on processes thought to be reflected by ACC activation. Finally, the *affective-motivational account* of the Ne/c focusses more on the affect that accompanies the occurrence of an error (Hajcak et al., 2004; Luu et al., 2003). This account does not contradict any of the other presented accounts, but emphasises that the Ne/c may reflect the affective response to an error more than it reflects error detection, response conflict, or reinforcement learning (Nuñez-Estupiñan et al., 2022). An important aspect that all accounts of the Ne/c presented here have in common is that it may signal the need to allocate more cognitive control to ongoing processes (Cavanagh & Frank, 2014), potentially improving future performance (Hester et al., 2005).

2.2 The error positivity

The error positivity (Pe) is an ERP component with a centro-parietal scalp distribution and a positive peak at around 200 to 400 ms after an erroneous response (Gehring et al., 2012). If the positive deflection follows a correct response, it is referred to as correct positivity (Pc; Imburgio et al., 2020). As for the Ne/c, I will use the term Pe/c to refer to the positive deflection following a response, regardless of whether the response was correct or erroneous.

Like the Ne/c, the Pe/c is larger for errors than for correct responses (Nieuwenhuis et al., 2001). More importantly, the Pe/c is larger for errors that were reported as errors by participants than for errors that were reported as correct responses (Endrass et al., 2005; Nieuwenhuis et al., 2001; Shalgi et al., 2009), suggesting that the Pe/c reflects *error awareness*. Expanding the dichotomous conception of aware versus unaware errors, a second account of the Pe/c emphasises the role of the continuous process that produces error awareness. This *error evidence accumulation* account (Steinhauser & Yeung, 2010, 2012) assumes that the cognitive system samples information about whether a given response was correct or an error. Information suggesting that the response was an error is referred to as error evidence. In this framework, the Pe/c is an indicator of how much error evidence has been accumulated. Error awareness consequently emerges when enough evidence has been accumulated. This interpretation of the Pe/c is further supported by findings that the Pe/c amplitude increases gradually as participants report an error with more confidence (Boldt & Yeung, 2015).

The Ne/c and Pe/c seem to reflect two dissociable response monitoring systems (Di Gregorio et al., 2018; Overbeek et al., 2005). For example, the Pe/c – but not the Ne/c – is modulated by error awareness (Nieuwenhuis et al., 2001). Some studies have suggested that although the Ne/c itself does not reflect error awareness, it may serve as input to an error evidence accumulation process (Wessel et al., 2011; Wessel, 2012). While Ne/c may thus contribute to the emergence of error awareness, it is not a necessary prerequisite. In fact, it has been shown that a Pe/c may occur without a preceding Ne/c (Di Gregorio et al., 2018). Hence, despite some similarities (Endrass et al., 2007; Herrmann et al., 2004), the Ne/c and Pe/c reflect functionally different response monitoring processes (Di Gregorio et al., 2018).

3 Perfectionism-related variations in response monitoring

When neural markers of response monitoring like the Ne/c or the Pe/c are quantified on the inter-individual level, they can be treated as measures of individual differences and be related to other individual differences. This approach allows to draw conclusions about neural underpinnings of personality traits. One personality trait that is particularly interesting in relation to response monitoring is perfectionism, i.e. the relatively stable disposition to strive for flawlessness (Stoeber, 2018). Perfectionistic individuals are characterised by setting themselves exceedingly high goals and being overly critical when evaluating their performance (Frost et al., 1990). Hence, response monitoring should be highly important for perfectionists.

3.1 Dimensions of perfectionism

Perfectionism is usually studied as a multidimensional construct (Feher et al., 2020; Frost et al., 1990; Hewitt & Flett, 1991; Stoeber & Otto, 2006). Early studies suggested different numbers of perfectionism dimensions (e.g. 6: Frost et al., 1990; 3: Hewitt & Flett, 1991). However, researchers soon converged to study two principal dimensions of perfectionism (Frost et al., 1993; Slade & Owens, 1998; Stoeber & Otto, 2006): Personal standards perfectionism (PSP) and evaluative concern perfectionism (ECP). (Note, however, that there is continuous research on different numbers of dimensions, e.g. Feher et al., 2020; Smith et al., 2016).

Personal standards perfectionists set highly demanding goals for themselves and strive to achieve these goals (Frost et al., 1990). They are largely internally motivated (Gucciardi et al., 2012; Longbottom et al., 2012; Stoeber et al., 2009) and are driven by the hope of success (Frost & Henderson, 1991; Stoeber & Becker, 2008). Furthermore, they display an approach orientation (Madigan et al., 2017; Stoeber, 2011), a positive self-assessment (Taylor et al., 2016) and they report feelings of pride (Stoeber et al., 2008) and satisfaction (Stoeber & Yang, 2010) when they have achieved their goals.

Evaluative concern perfectionists, on the other hand, are mostly externally motivated (Gucciardi et al., 2012; Longbottom et al., 2012; Stoeber et al., 2009). Fear of failure plays an important part in evaluative concern perfectionists' motivation, emotion, and cognition (Flett et al., 2016). The primary goal underlying EC perfectionists' striving for flawlessness is to avoid failure (Conroy et al., 2007; Kaye et al., 2008; Sagar & Stoeber, 2009). Based on relationships of ECP with worry (Flaxman et al., 2018; Santanello & Gardner, 2007), rumination (Flett et al., 2002; van der Kaap-Deeder et al., 2016), and an attentional bias to negative stimuli (Besser et al., 2004; Tonta et al., 2019), EC perfectionists have been hypothesised to be afraid of negative evaluations by others in case of failure, to display hypervigilance to cues of failure and to have a good memory for past instances of failure (Flett et al., 2016).

Both dimensions of perfectionism are related to a series of psychological disorders. PSP is a predictor for eating disorders such as anorexia nervosa (Wade et al., 2008) and bulimia nervosa (Lilenfeld et al., 2000; Steele et al., 2007). ECP, too, is a predictor for these eating disorders (Sassaroli et al., 2008), but also for depression (Enns et al., 2001), anxiety disorders (Antony et al., 1998), and obsessive-compulsive disorder (Suzuki, 2005; for a review on the relationship between perfectionism and psychological disorders, see Egan et al., 2011; for a meta-analysis, see Limburg et al., 2017). Considering these relationships, perfectionism has been argued to be a transdiagnostic factor for psychopathology (Egan et al., 2011; Limburg et al., 2017), suggesting that this personality trait comprises cognitions and behaviours that promote and maintain multiple psychological disorders (Harvey et al., 2004; Rodriguez-Seijas et al., 2015) and may thus be a suitable target for therapeutic interventions (Egan et al., 2014).

3.2 The 2x2 model of perfectionism

A popular and widely studied model of perfectionism is the *2x2 model* proposed by Gaudreau and Thompson (2010). Similar to other models, it is based on the two core dimensions of perfectionism outlined above: PSP and ECP. The key advancement of the 2x2 model, however, is that it also considers within-person combinations of PSP and ECP. By combining PSP and ECP intra-individually, four “subtypes” of perfectionism can be identified: pure-PS perfectionists (high PSP, low ECP), pure-EC perfectionists (low PSP, high ECP), non-perfectionists (low PSP, low ECP), and mixed perfectionists (high PSP, high ECP). It is important to highlight that despite the term “subtypes”, the model assumes fully continuous measures of PSP and ECP (Gaudreau, 2012, 2013). Each person is characterised by their position on a plane defined by PSP on one axis and ECP on the other axis of a coordinate system. This two-dimensional location is continuous by nature, but can roughly be assigned to one of the “subtypes” mentioned above to facilitate interpretation and communication (without actually splitting the continuous measures). Statistically speaking, the model considers a main effect of PSP, a main effect of ECP, and an interaction effect of PSP and ECP (Gaudreau, 2012).

The model makes a series of predictions regarding adaptive outcomes like well-being, achievement, positive self-evaluations etc. in relation to the different perfectionism “subtypes”. Pure-EC perfectionism is hypothesised to be associated with the worst outcomes. Mixed perfectionism is predicted to be related to somewhat better outcomes than pure-EC perfectionism because unlike in pure-EC perfectionism, PSP and thus internal motivation to perform flawlessly are high. Finally, the model predicts that pure-PS perfectionism is associated with better outcomes than mixed perfectionism (Gaudreau et al., 2018; Gaudreau & Thompson, 2010). Regarding the comparison of non-perfectionism with pure-PS perfectionism in terms of adaptive outcomes, the authors of the model initially proposed three hypotheses reflecting every possible pattern of results (non-perfectionism is associated with better/worse/not significantly different outcomes than pure-PS perfectionism) because empirical evidence was lacking and theoretical reasoning allowed for any of the three hypotheses (Gaudreau & Thompson, 2010). Ever since the model was first proposed, most support was found for the hypotheses that pure-PS perfectionism was associated with better outcomes than non-perfectionism (e.g. Hill, 2013; Madigan et al., 2016; Waleriańczyk et al., 2022) but some studies also found that pure-PS perfectionism was associated with worse outcomes (Hill et al., 2020). To solve this inconsistency, Gaudreau et al. (2018) recently presented the *differential susceptibility hypothesis* (Belsky et al., 2007; Belsky & Pluess, 2009) which aims at explaining under which circumstances pure-PS perfectionism is associated with better outcomes than non-perfectionism and under which circumstances it is associated with worse outcomes. According to this hypothesis, pure-PS perfectionists are more susceptible to both positive and negative influences in the environment than non-perfectionists. When pure-PS perfectionists are exposed to supportive environments, they may display better outcomes than non-perfectionists. When they are confronted with adverse environments, they may show worse outcomes. In this context, a supportive (adverse) environment refers to the absence (presence) of external stressors or flawed performance. For example, previous studies found that higher levels of PSP were associated with experiencing more pride and satisfaction following success or perfect outcomes than lower levels of PSP, whereas they were associated with experiencing more shame, guilt, and dissatisfaction following failure or flawed outcomes compared to lower levels of PSP (Stoeber et al., 2008; Stoeber & Yang, 2010).

3.3 Perfectionism and response monitoring

Studying response monitoring in perfectionism is particularly interesting because on the one hand, response monitoring is an important cognitive mechanism to ensure good performance. Perfectionists should thus aim at adopting effective response monitoring. On the other hand, response monitoring may confront perfectionists with their imperfect behaviour. Response monitoring may thus be an ambivalent mechanism for perfectionists.

The 2x2 model is particularly useful to study response monitoring in perfectionists because it takes the intra-individual combination of PSP and ECP into account. It highlights that effects of ECP on indicators of response monitoring may be different depending on whether PSP is high or low, and vice versa. Indeed, previous studies have found modulatory effects of one perfectionism dimension on the other dimension. For example, Stahl et al. (2015) found that the difference between the error negativity and the correct negativity was largest for mixed perfectionists, followed by non-perfectionists and pure-PS perfectionists. For pure-EC perfectionists, the Ne-Nc difference was close to zero. Similarly, Barke et al. (2017) observed most post-error slowing – a phenomenon which is thought to reflect adaptive post-error processes (Wessel, 2018) – for mixed-perfectionists and least post-error slowing for pure-EC perfectionists. Since ECP is high for both "subtypes", simply correlating ECP with post-error slowing would not have uncovered these perfectionism-related variations in post-error slowing. Hence, the 2x2 model helps to unveil effects of PSP and ECP on response monitoring that might go unnoticed in bivariate correlations.

3.4 Summary of Study 1

In the first study (Mattes et al., 2023), we investigated the relationship between response monitoring and perfectionism. We examined response monitoring using the error negativity amplitude and the error positivity amplitude and we conceptualised perfectionism in terms of the 2x2 model of perfectionism (Gaudreau & Thompson, 2010).

Method. Unlike previous studies that used relatively simple two-choice tasks (Barke et al., 2017; Drizinsky et al., 2016; Pieters et al., 2007; Schrijvers et al., 2010; Stahl et al., 2015; Tops et al., 2013), we employed a task with a more complex response selection (Porth et al., 2022; Stahl et al., 2020). Participants had to choose the correct response from eight possible response options. Furthermore, on each trial, participants had to evaluate their response on an eight-point scale ranging from “certainly right” to “certainly wrong”. With this task, we aimed at addressing the issue that despite numerous reports that (pure-PS) perfectionism is associated with better performance (see for example meta-analyses by Madigan, 2019, or Hill et al., 2018), none of the studies referenced above found a relationship between perfectionism and the proportion of correct responses. We suspected that previous findings might be affected by a ceiling effect that is grounded in the simplicity of the employed two-choice tasks. Hence, in our study, we employed a more challenging task to avoid this ceiling effect.

Results. Indeed, we found that ECP was associated with the error rate: The higher participants scored on ECP, the more errors they made. Interestingly, ECP was also associated with a tendency to evaluate responses as wrong, regardless of whether the response was actually correct or incorrect. Finally, we found that only participants with low to medium levels of ECP showed post-error slowing. Participants high in ECP did not show a significantly more slowing after errors than after correct responses.

On an electrophysiological level, we found a three-way interaction between PSP, ECP, and response accuracy on the Ne/c amplitude. Simple slope analyses revealed that the Ne-Nc difference was largest for non-perfectionists and mixed perfectionists, followed by pure-PS perfectionists. For pure-EC perfectionists, the Ne-Nc difference was very small and for the most part not statistically significant (see Figure 3D in Mattes et al., 2023). In other words, while there was significant error-specific activity in non-perfectionism, mixed perfectionism, and pure-PS perfectionism, there was no such error-specific activity in pure-EC perfectionism. Furthermore, we found that the difference in Pe/c amplitude between errors and correct responses (Pe > Pc) was modulated by ECP. The higher ECP was, the smaller the difference was between the Pe amplitude and the Pc amplitude. For high levels of ECP, the difference was not statistically significant.

Discussion. Our results provide further support for the notion that ECP is associated with rather negative outcomes. ECP was associated with a poorer performance (indicated by the error rate), poorer post-response adaptation (indicated by post-error slowing), and – when PSP was low –poorer early response monitoring (indicated by the Ne/c amplitude). Surprisingly, we did not find convincing evidence for the adaptive nature of PSP. We expected that high-PS perfectionists would draw on response monitoring to optimise their behaviour. For example, Stahl et al. (2015) reported increased post-error accuracy for high-PS perfectionists and Barke et al. (2017) found increased brain activity in the putamen for high-PS perfectionists – a brain area that is associated with post-response adaptation (Hester et al., 2009; Linke et al., 2010). The only evidence for an adaptive nature of PSP in our study was that PSP seemed to alleviate some of the negative aspects of ECP in early response monitoring. Specifically, while pure-PS perfectionists (high ECP, *low* PSP) showed no or only very little early response monitoring, mixed perfectionists (high ECP, *high* PSP) did show substantial early response monitoring in terms of the Ne/c amplitude. It seems that the presence of PSP mitigates some of the detrimental effects of high ECP on response monitoring.

3.5 Conceptual contributions of Study 1

Our study makes multiple contributions to the literature. First, we replicated the key finding by Stahl et al. (2015) regarding the Ne-Nc amplitude difference: The difference was the largest for non-perfectionism and mixed perfectionism, and close to zero for pure-EC perfectionism. In light of the replication crisis in psychology and related disciplines (Open Science Collaboration, 2015), it is important to ensure replicability of scientific findings.

The successful replication in our study strengthens our confidence in the perfectionism-related effects on the Ne/c amplitude.

Second, our study was the first study to employ a task with a more complex response selection to examine perfectionism-related variations in response monitoring. This task allowed us to obtain a higher number of error trials and thus more precise indicators of response monitoring on error trials (error rate: Mattes et al., 2023: 22 %; Drizinsky et al., 2016: 16 % in the 100 ms SOA condition; Barke et al., 2017: 15 %; Stahl et al., 2015: 8 %). More importantly, we found an association of ECP and the error rate, suggesting that we successfully circumvented the ceiling effect that may have been present in previous studies. Due to the more challenging nature of the task, perfectionism-related differences in behaviour and response monitoring may become more apparent than in simpler two-choice tasks.

Third, after about a decade of largely exploratory research in the field, we took the opportunity to develop a model of response monitoring in perfectionists by integrating findings and suggestions from previous literature and the results of our current study. In the case of ECP, we presented two competing models, one of which is favoured by the results of our study. The models are illustrated in Figure 5 in Mattes et al. (2023). We described how these models could be tested against each other. Overall, our study may mark the transition from initial exploratory research in the field of perfectionism and response monitoring to more confirmatory research.

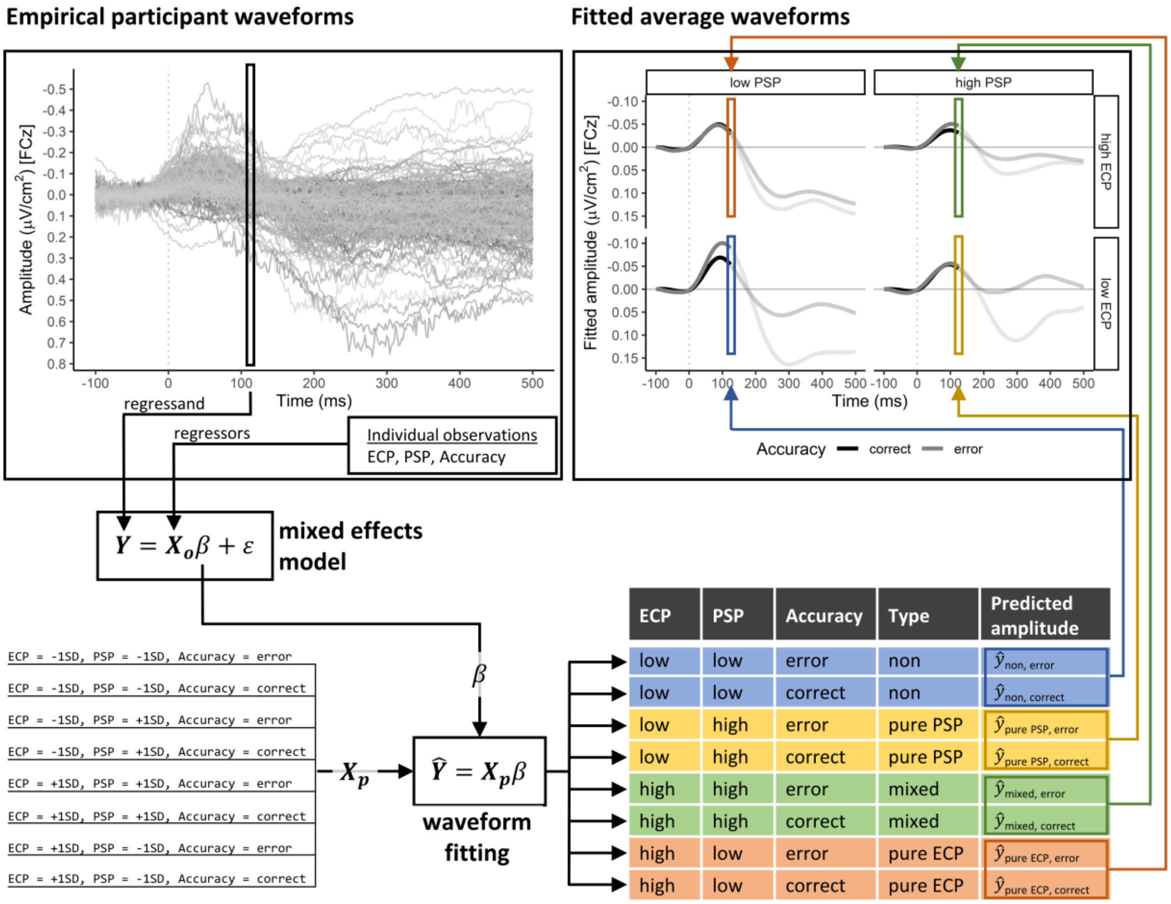
3.6 Methodological contributions of Study 1

Apart from these benefits, our study comprises some methodological advancements. First, we studied indicators of error detection derived from signal detection theory (Green & Swets, 1966) to decompose the self-report evaluation of participants' responses into independent measures of sensitivity and bias: One measure captured participants' ability to correctly evaluate the accuracy of their responses (sensitivity) and the other measure captured participants' tendency to evaluate their responses as errors, regardless of the actual accuracy of their response (bias). This approach helped us discover that high-EC perfectionists report more often that their response was incorrect without actually being able to better discriminate between errors and correct responses.

The second methodological advancement addresses an issue that arises when researchers intend to study ERP waveforms for the perfectionism "subtypes". In this case, researchers inevitably split the data into four groups (often based on somewhat arbitrary values like the median) and plot the waveforms for each group. However, this approach is inconsistent with the main analyses in which PSP and ECP are treated as continuous variables and are not artificially split into groups. For example, Stahl et al. (2015) lament that some of the results of their simple slope analyses were not as clearly visible in the waveforms for the perfectionism "subtypes". In our study, we developed an approach that allowed to visualise the "subtype" waveforms in a way that is more consistent with the analyses they aim to illustrate. To obtain the waveforms, a series of mixed-effects models are computed for each time point of the waveform (Figure 3). For example, if the waveform covers an interval from -100 ms before response onset to 500 ms after response onset and the EEG signal was recorded at a sampling rate of 500 Hz, the interval comprises 300 time points for each of which a mixed-effects model is computed. The model predicts the respective ERP amplitude by PSP, ECP, response accuracy, and all possible interactions. Next, each mixed-effects model is used to predict the respective ERP amplitude for all possible combinations of high and low PSP and ECP (mean plus/minus one standard deviation) and response accuracy (error and correct), providing the predicted waveforms for each of the four perfectionism "subtypes" for errors and correct responses. Since both the waveforms and the simple slope analyses are based on the same mixed-effects model and

Figure 3

Waveform fitting procedure



$Y = X_o\beta + \varepsilon$

$\hat{Y} = X_p\beta$

ECP = -1SD, PSP = -1SD, Accuracy = error
ECP = -1SD, PSP = -1SD, Accuracy = correct
ECP = -1SD, PSP = +1SD, Accuracy = error
ECP = -1SD, PSP = +1SD, Accuracy = correct
ECP = +1SD, PSP = +1SD, Accuracy = error
ECP = +1SD, PSP = +1SD, Accuracy = correct
ECP = +1SD, PSP = -1SD, Accuracy = error
ECP = +1SD, PSP = -1SD, Accuracy = correct

ECP	PSP	Accuracy	Type	Predicted amplitude
low	low	error	non	$\hat{y}_{\text{non, error}}$
low	low	correct	non	$\hat{y}_{\text{non, correct}}$
low	high	error	pure PSP	$\hat{y}_{\text{pure PSP, error}}$
low	high	correct	pure PSP	$\hat{y}_{\text{pure PSP, correct}}$
high	high	error	mixed	$\hat{y}_{\text{mixed, error}}$
high	high	correct	mixed	$\hat{y}_{\text{mixed, correct}}$
high	low	error	pure ECP	$\hat{y}_{\text{pure ECP, error}}$
high	low	correct	pure ECP	$\hat{y}_{\text{pure ECP, correct}}$

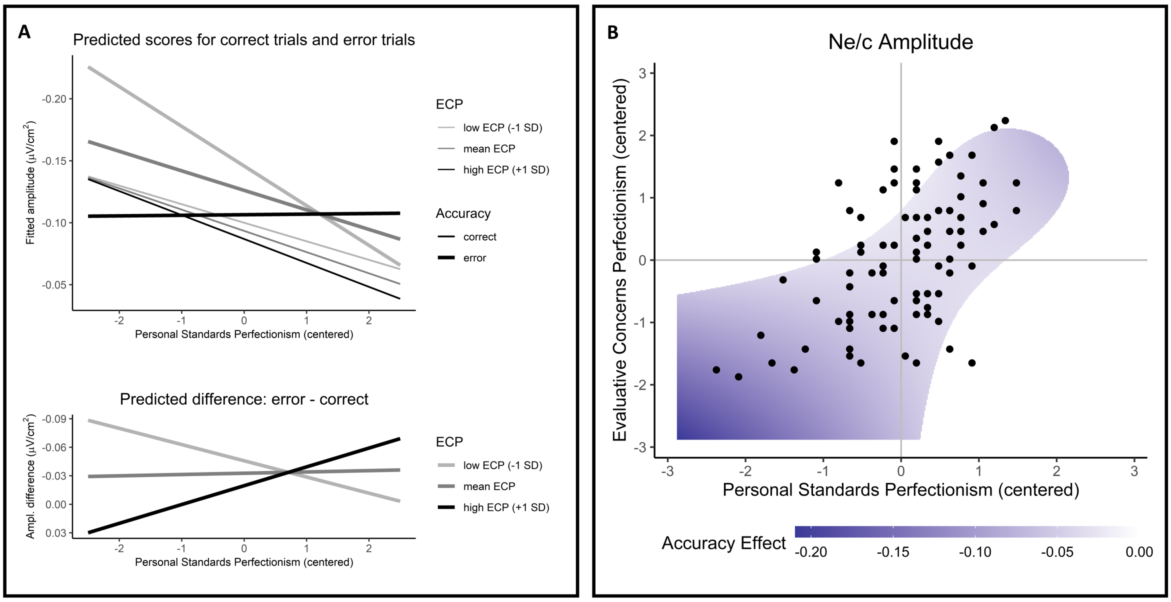
Note. To obtain the fitted waveforms for the perfectionism “subtypes”, the following procedure is repeated for every time point. The illustration shows the sequence of computations for time point $t = 110$ (ms). First, the empirical amplitudes at a given time point (regressand vector $\boldsymbol{Y}$) are submitted to a mixed effects regression analysis and predicted by the individual observations of evaluative concerns perfectionism (ECP), personal standards perfectionism (PSP), response accuracy, and all possible interactions (observed regressor matrix $\boldsymbol{X_o}$). The resulting model coefficients (vector β) are then used to compute predicted amplitudes (vector $\widehat{\boldsymbol{Y}}$) for all combinations of high (+1SD) and low (-1SD) values of PSP and ECP, and for errors and correct responses (matrix $\boldsymbol{X_p}$). Once the entire procedure has been applied to every time point, fitted waveforms can be plotted for the perfectionism “subtypes” for errors and correct responses based on the respective, predicted amplitude values.

the same data (i.e. the full dataset, not a subset of the data), they will allow to draw the same conclusions. Hence, this visualisation method is more apt to illustrate the results of the analyses than methods based on split data.

Another challenge in research designs involving two continuous variables (PSP and ECP) and one categorical variable (response accuracy) is the interpretation of significant three-way interactions. So far, this type of interaction has been disentangled by assigning one perfectionism dimension the formal role of the key predictor (e.g. PSP) and the other dimension the formal role of the moderator (e.g. ECP). Next, simple slopes between PSP and the dependent variable were computed for three different values of ECP (mostly the mean minus one standard deviation, the mean, and the mean plus one standard deviation) and the resulting three regression lines were plotted. This procedure was conducted separately for correct responses, errors, and the difference score between errors and correct responses, resulting in three plots containing three regression lines each (e.g. Barke et al., 2017; Stahl et al., 2015). This conventional way of displaying three-way interactions of PSP, ECP, and accuracy is displayed in Figure 4A. While these plots allow to better understand the three-way interaction, they do not directly answer what the researchers desired to find out: How are differences in the DV between errors and correct responses related to within-participant PSP-by-ECP combinations? To address this question more comprehensibly, we developed a new type of figure and accompanying analysis (see Figure 4B). This type of figure displays PSP on the x-axis and ECP on the y-axis. Considering both perfectionism dimensions as moderators of the response accuracy effect on the DV (i.e. the difference between errors and correct responses), we computed simple slopes for the response accuracy factor for all sensible PSP-by-ECP combinations. The resulting simple slopes were colour-coded in the figure. This way, it is immediately visible how the accuracy effect changes as a function of PSP and ECP. Furthermore, if only simple slopes are plotted that reach the

Figure 4

Approaches to interpreting three-way interactions involving two continuous and one categorical predictor



Note. (A) Conventional approach to interpret three-way interactions. Here, personal standards perfectionism (PSP) acts as the main predictor and evaluative concerns perfectionism (ECP) acts as the moderator. The relationship between PSP and the dependent variable (DV) is computed for low (mean – 1SD), medium (mean) and high (mean + 1SD) levels of ECP for errors, correct responses, and the error-correct difference. (B) Novel and more intuitive approach to interpret three-way interactions (see also Figure 3D in Mattes et al., 2023). For each PSP-by-ECP combination, the difference in the DV between errors and correct responses is computed and colour coded. The darker the blue is, the larger the difference is. White represents insignificant differences.

level of statistical significance, the Johnson-Neyman interval becomes visible. The Johnson-Neyman interval indicates for which values of the moderator the slope for the key predictor becomes statistically significant (Johnson & Neyman, 1936). Unlike in a two-way interaction with one moderator, the Johnson-Neyman interval for a three-way interaction with two moderators is not defined by two values on a one-dimensional variable (Johnson & Neyman, 1936) but by a (non-linear) line on a two-dimensional plane. Conventional illustrations like Figure 4A, that were used in Stahl et al. (2015) and Barke et al. (2017), do not allow to identify the Johnson-Neyman interval considering both perfectionism dimensions as moderators. From our proposed new figure type, however, it quickly becomes obvious for which values of PSP and ECP there is a significant effect of response accuracy. This methodological improvement facilitates the understanding and interpretation of three-way interactions.

In sum, the first study of my dissertation demonstrates the utility of studying response monitoring on a higher level (participant-level). By employing advanced methodological approaches, we were able to identify clear patterns of response monitoring that were differentially associated with the two perfectionism dimensions. We were able to corroborate previous findings through replication and provide new insights into processing mechanisms in perfectionists.

4 Linking response monitoring and post-response adaptation

Response monitoring may not only differ *between* individuals, but also *within* individuals. At times, an individual may display more successful response monitoring. At other times, they may be less successful at monitoring their responses. It is sensible to assume that whether response monitoring is more or less successful systematically relates to other cognitive processes. For example, instances of successful response monitoring should translate to an improvement in subsequent performance because successful response monitoring facilitates detecting deviations from intended responses, paving the way to implement strategies that prevent these deviations from reoccurring (Wessel, 2018). This mechanism is termed post-response adaptation.

4.1 Markers and accounts of post-response adaptation

Post-response adaptation refers to the observation that current behaviour and outcomes of the current behaviour modulate subsequent behaviour and cognitive processes. The two most prominent markers of post-response adaptation are post-response time and post-response accuracy, i.e. the response time and the probability of a correct response on trial $n + 1$, respectively.

Following errors, response times are often increased, an observation that has been termed *post-error slowing* (Laming, 1968; Rabbitt, 1966). Increased response times on trials following errors have been suggested to reflect increased response caution as a measure to prevent future errors (Botvinick et al., 2001; Rabbitt & Rodgers, 1977). However, if prolonged response times succeeding errors were indeed due to more response caution, post-error responses should also have a higher probability of being correct than post-correct responses. While there are numerous studies that find increased post-error accuracy (e.g. Beatty et al., 2020; Danielmeier et al., 2011; Grützmann et al., 2014; Laming, 1979) supporting the *response caution account* of post-error slowing, a substantial body of literature finds no change in post-error accuracy (e.g. Hajcak et al., 2003; King et al., 2010; Moran et al., 2015) or even a lower probability of giving a correct response on the post-error trial (e.g. Fiehler et al., 2005; Houtman & Notebaert, 2013; Jentzsch & Dudschig, 2009; Notebaert et al., 2009). The latter finding has led researchers to question whether post-error slowing is really an adaptive mechanism. As an alternative explanation, Notebaert et al. (2009) have proposed the *orienting account* of post-error slowing that postulates that infrequent and thus unexpected events such as errors shift attention away from the task towards the source of the unexpected event. On the subsequent trials, the reduced attentional focus on the task itself prolongs response times and decreases the probability of a correct response (Houtman & Notebaert, 2013). Unlike the response caution account, the orienting account suggests that post-error slowing is an indicator of maladaptive mechanisms following errors. Whether post-error slowing reflects adaptive or maladaptive processes seems to depend on the time the cognitive system has to adjust itself after an error. When the experimental trials occur in rapid temporal succession (i.e. when response-stimulus intervals (RSI) are short, e.g. 50 ms), post-error slowing seems to reflect an orienting response and is often accompanied by a decreased post-response accuracy. When RSIs are long (e.g. 1,000 ms), post-error slowing may reflect more adaptive processes such as increased response caution and is accompanied by increased post-response accuracy (Dudschig & Jentzsch, 2009; Jentzsch & Dudschig, 2009). Recently, Wessel (2018) reconciled adaptive and maladaptive accounts of post-error slowing in the *adaptive orienting theory*. According to this theory, the occurrence of an error represents an expectancy violation (assuming that correct responses are more frequent than errors) triggering automatic and universal processes to unexpected events such as an orienting response. Once the source of the error has been identified, more controlled and adaptive processes that are specific to errors and to certain error types are initiated. For example, if the error has occurred because of an impulsive, premature response, more response caution is implemented. Depending on when in this sequence of events the new trial sets in, different behavioural patterns may be observed. If trial *n* + 1 starts while the automatic processes in response to unexpected events are still going on, post-response times will be prolonged and post-response accuracies decreased because the attentional focus is on identifying the source of expectancy violation. If trial *n* + 1 starts while the more controlled, adaptive processes are being executed, post-response times will still be prolonged because the attentional focus is on implementing the adaptive measures, but no effect on post-response accuracy may be found. If the more controlled, adaptive processes have finished at the onset of the subsequent trial, post-response accuracies will be increased, reflecting successful adjustment triggered by the occurrence of an error.

It should be noted that some studies reported a decrease in response times termed post-error speeding (e.g. King et al., 2010; Purcell & Kiani, 2016). While post-error slowing usually occurs in tasks in which response selection is relatively simple and errors are faster than correct responses, post-error speeding occurs in tasks with a more complex response selection and in which errors are slower than correct responses (Damaso et al., 2020; Novikov et al., 2017). Hence, whether post-error responses are slowed down or sped up seems to depend on the nature of the error itself. This is in line with studies that have found that post-response adaptation mechanisms seem to be specific to the error type, i.e. they tackle specifically those processes that were flawed and ultimately allowed for the error to occur (Maier et al., 2011; Wessel, 2018).

4.2 Special methods to study post-response adaptation

As has become clear in the previous section, traditional approaches to studying post-response adaptation rely on behavioural measures of post-response time and post-response accuracy. A more modern approach combines those behavioural measures in a computational model to extract model parameters that are supposed to reflect specific cognitive processes. The so called *diffusion model* (Ratcliff & McKoon, 2008) describes responses in binary speeded decision tasks using four key parameters. According to the diffusion model, evidence for one of the two possible decision outcomes is sample from the stimulus representation. Once a certain amount of evidence has been accumulated, the motor response is initiated and executed. The speed of the evidence accumulation process is captured by the drift rate parameter v. Higher drift rates indicate a faster evidence accumulation process. The amount of evidence that needs to be collected before a motor response is initiated is determined by the decision threshold parameter a. The higher the decision threshold is, the more evidence needs to be accumulated. The evidence accumulation may be biased towards one of the two possible responses. This bias is captured by the starting point parameter z. While the drift rate, decision threshold and starting point parameters jointly determine the decision time, a fourth parameter comprises all the processes that are not captured by the other three parameters and is consequently termed non-decision time t_0. The non-decision time includes for example stimulus perception and encoding, and motor response execution. Note that the full diffusion model may comprise three additional parameters for the across-trial variability of the drift rate, starting point and non-decision time (Ratcliff & Rouder, 1998). However, these variability parameters may be difficult to estimate reliably (Boehm et al., 2018) and fixing them to zero may improve the estimation of the remaining model parameters (Lerche & Voss, 2016).

The diffusion model allows to disentangle competing accounts for post-error slowing because the accounts make differential predictions about how diffusion model parameters differ between post-error and post-correct trials. For example, if post-error slowing indicated that participants were more cautious following errors, the decision threshold should be elevated on post-error compared to post-correct trials. An increased decision threshold indicates that more information is collected before a response is initiated, i.e. the response is selected with more caution (Dutilh et al., 2012). If post-error slowing was due to an orienting response, the attentional focus should be distracted from the task. Consequently, the drift rate should be smaller on post-error trials compared to post-correct trials, reflecting the fact that less cognitive resources are available for the task itself (Dutilh et al., 2012). Studies using the diffusion model to investigate post-response behaviour have found support for the response caution account (Dutilh et al., 2012; Schiffler et al., 2017). However, there is also evidence for the orienting account put forth by diffusion model studies (Purcell & Kiani, 2016; Schiffler et al., 2017). For example, Schiffler et al. (2017) examined not only the trial immediately following an error, but up to five trials succeeding errors. They found that the decision threshold was increased on all five trials following errors, but decreased with time, suggesting an adaptive and sustained adjustment to response caution. The drift rate, however, was only decreased on the trial that immediately followed the error. On the second to fifth trial after an error, the drift rate was higher (compared to the second to fifth trial after correct responses). This drift rate pattern suggests that there might indeed be an orienting response interfering with task-related processes on immediate post-error trials. Furthermore, the sustained increase in drift rate on the second to fifth trial after an error could reflect a successful reconfiguration of the taskset, i.e. the allocation of the attentional focus on the task-relevant features. This interpretation would be in line with the adaptive orienting theory (Wessel, 2018) which proposes reconfiguring the taskset as a controlled adaptive measure occurring at later stages of post-error adjustment, similar to increasing response caution. Hence, the diffusion model has proven very valuable for studying post-response adaptation.

A second popular method to study post-response adaptation involves ERPs. Researchers have linked indicators of error processing like the Ne/c or the Pe/c to *behavioural* measures of post-response adaptation. There is a substantial body of literature that suggests that an increased Ne/c peak amplitude is associated with more post-error slowing (Debener et al., 2005; Fischer et al., 2015; Gehring et al., 1993; Wessel et al., 2011; West & Travers, 2008), although other studies have failed to find this relationship (Endrass et al., 2007; Gehring & Fencsik, 2001; Núñez Castellar et al., 2010; Strozyk & Jentzsch, 2012). Alternatively, researchers have also linked the Ne/c and Pe/c to *electrophysiological* measures of post-response adaptation. For example, Buzzell et al. (2017) and Beatty et al. (2018) showed that post-error slowing may in fact be due to an overlap of response monitoring on trial *n* and perceptual processing on trial *n* + 1. They found that when the Ne (Beatty et al., 2018) or the Pe (Buzzell et al., 2017) were more pronounced, the P1 – an ERP component reflecting sensory processes – on the subsequent trial was diminished. Furthermore, the Ne and Pe amplitudes correlated with the P1 amplitude: the larger the Ne or Pe amplitudes on trial *n*, the smaller the P1 amplitude on trial *n* + 1.

4.3 Summary of Study 2

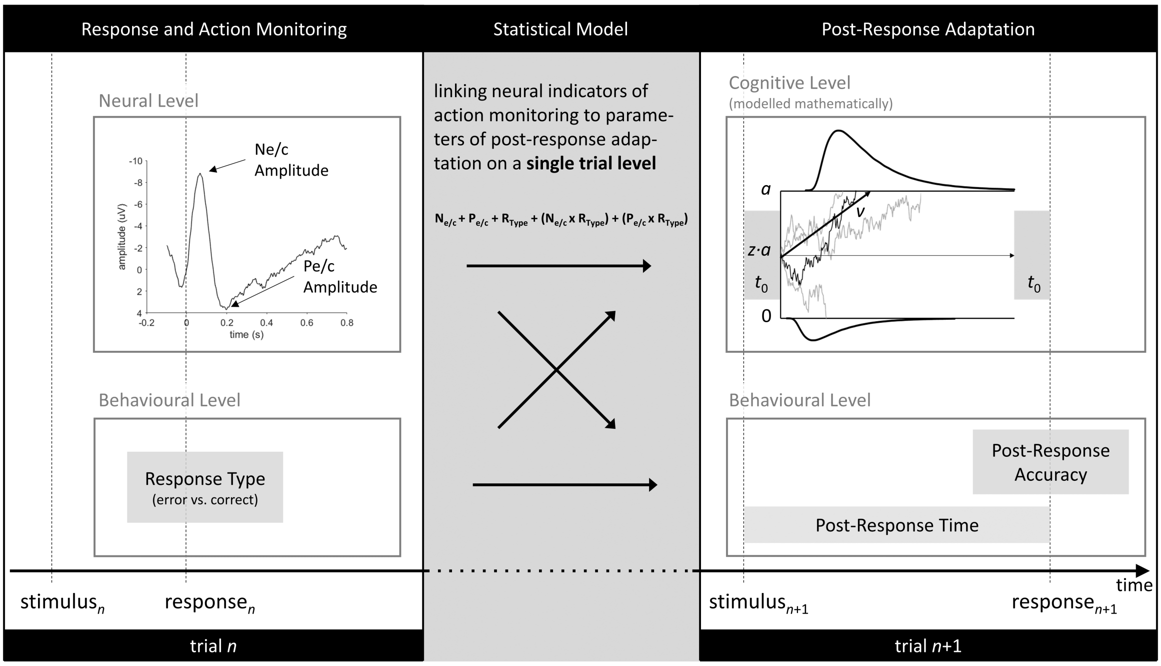
Previous research has linked behavioural indicators of post-response adaptation to preceding electrophysiological indicators of response monitoring and it has studied post-response adaptation in terms of the diffusion model. However, to our knowledge, no study has combined these two approaches yet. The second study (Mattes et al., 2022) aimed at filling this gap by linking response monitoring ERPs to the diffusion model parameters on the subsequent trial. This would allow us to understand more profoundly how post-response adaptation processes are modulated by the preceding Ne/c- and Pe/c-related processes.

Method. We estimated single-trial peak amplitudes of the Ne/c and Pe/c using a combination of wavelet-based signal denoising and single-trial waveform modelling (Hu et al., 2010; Hu et al., 2011). We then entered the amplitude estimates on trial *n* as predictors of the response time, response accuracy, and the diffusion model parameters on the subsequent trial (i.e. trial $n + 1$) in a (Bayesian) multilevel model. This n*euro-cognitive diffusion model of adaptive behaviour* is displayed in Figure 5. We analysed three existing datasets of Eriksen flanker tasks (Eriksen & Eriksen, 1974) that differed in their instruction to the participants (Bode & Stahl, 2014; Kummer et al., 2020; Stahl et al., 2015): Depending on the dataset, participants were instructed to respond as fast as possible, as accurate as possible, or to equally focus on response speed and accuracy.

Results and discussion. We found that in all three datasets, the Ne/c amplitude was associated with slower and more accurate responses on the following trial, suggesting that more intense early error processing is related to more successful post-response adaptation. In terms of the diffusion model parameters, larger Ne/c amplitudes on trial *n* were associated

Figure 5

A neuro-cognitive diffusion model for adaptive behaviour



Note. The neuro-cognitive diffusion model links single-trial Ne/c and Pe/c amplitudes on correct and erroneous trials to computationally derived parameters of post-response adaptation, i.e. the decision threshold (a), speed of evidence accumulation (v) and non-decision time (t_0) on the subsequent trial.

with an increased decision threshold and a higher drift rate on trial *n* + 1. While the increased threshold may reflect more response caution, the larger drift rate may indicate an increased attention to task-relevant features on trials following more intense early error processing. Both adaptations combined contribute to preventing future errors. Interestingly, we observed this pattern of results for both errors and correct responses. It thus seems that the Ne/c amplitude is an accuracy-independent indicator of response monitoring.

The Pe/c amplitude was related to faster responses and a lower decision threshold on the subsequent trial, but only in datasets in which response speed was relevant. The Pe/c-related process may thus aim at ensuring that responses are given in time, somewhat counteracting the Ne/c-related processes: It seems that both processes are linked to speed-accuracy adjustments on the subsequent trial. While the Ne/c-related process increases the decision threshold in favour of a higher response accuracy, the Pe/c-related process decreases the decision threshold in favour of faster responses. This mechanism may help to find the balance between the conflicting demands of response speed and response accuracy (see Figure 4 in Mattes et al., 2022).

To our knowledge, our study is the first study to combine single-trial ERP estimates and computational modelling of responses on subsequent trials to investigate the link between response monitoring and post-response adjustment. In doing so, our study sheds further light on the functional significance of the Ne/c and Pe/c and helps understand how response monitoring impacts subsequent behaviour.

4.4 Methodological contributions of Study 2

Our study has several methodological strengths that provide a strong foundation for the theoretical claims we make based on the results. First, we applied a thoughtfully constructed and validated procedure to estimate single-trial peak amplitudes for the Ne/c and Pe/c (Hu et al., 2010; Hu et al., 2011). This approach is of paramount importance because the mechanism we aimed to investigate – the link between response monitoring and post-response adaptation – acts on a single-trial level and thus requires single-trial peak estimates of ERP components. However, ERP peak amplitudes are usually quantified in an average waveform, i.e. after averaging single-trial waveforms, because the signal-to-noise ratio in the single-trial waveforms is too poor (Clayson et al., 2013; Luck, 2014) and improves by averaging single-trial waveforms because the unsystematic noise cancels out. The approach that we used tackled this challenge by combining a denoising procedure based on a wavelet filter and a regression-based modelling procedure of single-trial waveforms (for more details, see the original authors of the method; Hu et al., 2010; Hu et al., 2011; or our paper: Mattes et al., 2022, particularly Figure 3). Ultimately, this procedure allowed us to investigate the link between response monitoring and post-response adaptation on a single-trial level whereas some other researchers resorted to a between-subject analysis that is less adequate to study single-trial mechanisms (e.g. Hajcak et al., 2003).

The second methodological strength of our study is the combination of two state-of-the-art methods: single-trial peak estimation of ERP components and computational modelling of cognitive processes (Bridwell et al., 2018). Most previous studies on the research question predicted post-response time and post-response accuracy by the Ne/c and/or Pe/c amplitude of the preceding trial (e.g. Debener et al., 2005; Fischer et al., 2015; Hajcak et al., 2003). However, as we have delineated above, behavioural indicators of post-response adaptation are ambiguous and only allow to draw limited conclusions about the underlying cognitive processes. Computational models like the diffusion model help disentangle these processes. Hence, linking neurological indictors of response monitoring to indicators of post-response adaptation derived from computational models provides a more comprehensible insight than previous approaches.

Finally, it is important to note that we applied the analyses to three datasets and successfully replicated many findings, especially those relating to the Ne/c. The robustness of our findings provides a strong foundation for theoretical conclusions.

4.5 Conceptual contributions of Study 2

There is converging evidence that the Ne/c-related process is associated with post-error slowing. However, it was hitherto unclear whether this slowing was due to more response caution – which is widely considered an adaptive process – or an orienting response – which is rather considered a maladaptive process (Wessel, 2018). Our study provides convincing evidence that Ne/c-related variations in post-response time reflect adaptive processes such as increased response caution and a stronger focus on task-relevant features. Moreover, this association was found for both the *error* negativity (Ne) and the *correct* negativity (Nc), adding to a growing body of literature suggesting that the Ne/c is not an error-specific ERP component but reflects more general response monitoring (Hoffmann & Falkenstein, 2010; Roger et al., 2010).

Findings regarding the association between the Pe/c and post-response adaptation are more heterogeneous than for the Ne/c. Some studies report increased post-response times for higher Pe/c amplitudes (Fischer et al., 2015; Hajcak et al., 2003), other studies found no variation with post-response times (Beatty et al., 2018; Endrass et al., 2007). One study reported decreased post-response times related to larger Pe/c amplitudes (Buzzell et al., 2017). None of these studies, however, controlled for the impact of the Ne/c when investigating the Pe/c, although both ERP components occur temporally and spatially close to each other, potentially producing a certain amount of overlap. By including both ERP components in the same statistical model when predicting post-response adaptation parameters, we were able to isolate the Ne/c- and Pe/c-specific contribution to post-response adaptation parameters. Furthermore, since we analysed three datasets that employed a similar experimental task but differed in terms of the instruction (focus on response speed vs. focus on response accuracy vs. both equally important), we were able to relate variations in the link between the Pe/c and post-response adaptation to variations in these instructions. Ultimately, these advances allowed us to obtain a more complete understanding of how the Ne/c- and Pe/c-related processes interact with each other with regards to post-response adaptation (see Figure 4 in Mattes et al., 2022).

To sum up, we combined two state-of-the-art neuroscientific methods to investigate the link between response monitoring and post-response adaptation. Several methodological advantages strengthen our confidence in the findings. The results of our study suggest that early response monitoring indicated by the Ne/c-related process is associated with successful post-response adaptation in terms of an increased decision threshold and a stronger focus on task-relevant features. Later response monitoring indicated by the Pe/c-related process seems to be associated with ensuring that subsequent responses are given with an adequate response speed. The Ne/c- and Pe/c-related processes may thus jointly determine speed-accuracy adjustments in the subsequent trial.

5 Concluding remarks

In two studies, we investigated response monitoring on different levels: The first study asked how differences in response monitoring *between* participants relate to different degrees of perfectionism displayed by the participants (Mattes et al., 2023). The second study investigated how differences in response monitoring *within* participants impact subsequent adaptive behaviour (Mattes et al., 2022).

5.1 Summary and future directions

Both studies have in common that they contribute to the current literature by proposing models of response monitoring on different levels. Study 1 delineates two competing hypotheses of response monitoring in EC perfectionists (illustrated in Figure 5 in Mattes et al., 2023) and provides an initial attempt to dissociate both accounts in the current data. Study 2 describes a potential adaptation mechanism that ensures that responses are both accurate and in time, and identifies the differential involvement of early and late response monitoring in this mechanism (illustrated in Figure 4 in Mattes et al., 2022). By integrating the respective individual findings in a model, both studies provide opportunities for future research to derive and test specific hypotheses, providing more evidence in favour of the models, potentially falsifying the models, or modifying and expanding the models based on new findings.

Apart from theoretical contributions, the two studies also make important methodological contributions to the respective field of research. Study 1 provides more intuitive ways of understanding three-way interactions that involve two continuous variables, facilitating the interpretation of effects of response accuracy as a function of PSP and ECP. Study 2 combines single-trial ERP analysis with a diffusion model decomposition of post-response behaviour to better understand post-response processes on a trial-by-trial basis. The methodological advances of both studies allow to obtain more detailed insights than conventional methods could provide.

While both studies focussed exclusively on one level of response monitoring, future research may benefit from combining both levels. By integrating the intra-individual and inter-individual level of response monitoring, research may provide a more complete picture of how post-response adaptation mechanisms differ between different types/dimensions of perfectionism. For example, the link between response monitoring and post-response adaptation may be stronger for high-PS perfectionists than low-PS or high-EC perfectionists due to the stronger internal motivation (Longbottom et al., 2012) and hope of success (Frost & Henderson, 1991; Stoeber & Becker, 2008) of high-PS perfectionists (Stoeber et al., 2018). Although we did not find any differences in post-response time and post-response accuracy regarding PSP on the inter-individual level in Study 1, there may still be PSP-related variations on the intra-individual level. Using the terminology of multilevel modelling in statistics, the described effect is a *cross-level interaction* (Aguinis et al., 2013), i.e. the strength or direction of relationships on a lower level (here: the link between response monitoring and post-response adaptation) systematically varies with variables or constructs that are assessed on a higher level (here: perfectionism). Importantly, a cross-level interaction does not require the existence of a main effect on the higher level. Hence, despite the lack of a relationship between PSP and post-response behaviour (at least in our study), it could be hypothesised that early response monitoring is more strongly related to an increased decision threshold in high-PS perfectionists than in low-PS perfectionists. In Study 1, we expected that PSP was associated with response optimisation. Unlike in other studies (Barke et al., 2017; Ridderinkhof et al., 2004; Stahl et al., 2015), we found no evidence for this hypothesis in the analyses we conducted in the context of Study 1. However, optimised performance would not only be reflected in improved *overt* performance, but also in terms of more efficient and/or more effective *covert* mechanisms such as trial-by-trial post-response adaptation. For ECP, investigating a potential cross-level interaction would be particularly interesting. In our study, ECP was associated with a poorer task performance in terms of an elevated error rate. Perhaps, the adaptation mechanism we identified in Study 2 is impaired in high-EC perfectionists, which could explain the higher error rate we found in Study 1. Hence, applying the methodological approach from Study 2 to the research questions from Study 1 would be highly suitable to expand our knowledge on cognitive processes in perfectionists. These considerations demonstrate how the methodological integration of both studies presented here and the integration of both levels of response monitoring could provide novel and promising insights.

5.2 Limitations

Despite the many strengths of both studies, they also have some limitations. For example, the proposed models describing response monitoring in perfectionists and the link between response monitoring and post-response adaptation are mostly based on post-hoc interpretations of the data. While this is a valid approach to put forth theoretical advances, it would be highly desirable to design studies that specifically test the proposed models and to conduct confirmatory analyses on them. Such studies would also allow to investigate the competing hypotheses of response monitoring in EC perfectionists more differentially. Although the results of Study 1 seem to favour one of the hypotheses, they are not fully conclusive because the study was not specifically designed to disentangle both hypotheses.

As is the case in the large majority of neurocognitive studies, our studies mostly employed linear models to investigate relationships of response monitoring with perfectionism and post-response adaptation. However, it is questionable whether this implicit assumption of linearity holds for all markers that we (and other researchers) studied. For example, a linear positive relationship between PSP and performance suggests that individuals particularly high in PSP display the best performance. Yet, it is theoretically plausible that extremely high levels of PSP – just like extremely low levels of PSP – are associated with worse outcomes (Nordin-Bates & Abrahamsen, 2016). A curvilinear function like a parabola (inverted-U shape) may be more suitable to describe the relationship of PSP with many markers of performance and response monitoring. Perhaps, this parabola may even be asymmetric with a smaller slope to the left compared to the right of the vertex of the parabola, indicating that positive outcomes like performance increase with increasing levels of PSP, then reach a maximum at medium to high levels of PSP and rapidly drop for extremely high levels of PSP. In a similar fashion, it may be called into doubt that single-trial estimates of the Ne/c or Pe/c amplitude are linearly related to markers of post-response adaptation like the post-response decision threshold. The decision threshold (just like the drift rate) may not be raised or lowered indefinitely. Hence, a sinusoidal relationship may be more sensible to assume. However, although non-linear relationships are plausible and perhaps even more likely in many research scenarios, linear models are a valid and even necessary tool to simplify complex relationships, making the investigation of these relationships possible in the first place.

A further issue emerges from the complexity of the multilevel models and computational models that were employed in our studies. Taking the naturally occurring multilevel structure of neurocognitive data into account in the statistical analyses requires researchers to make certain assumptions and decisions, e.g. regarding the random effects structure in multilevel models or regarding the parameters to include and to estimate in the diffusion model. These assumptions may impact the results. In our studies, we took several measures to address this issue. For example, we computed and compared fit indices for the multilevel models in Study 1 to determine the random effects structure (Matuschek et al., 2017), and assessed whether the estimated diffusion model parameters in Study 2 were able to adequately describe the observed response times and response proportions (Wiecki et al., 2013). Where necessary, we provided theoretical considerations to justify the assumptions. Despite these efforts, it is important to not only consider the results of such models, but also their structure when appraising the results.

5.3 Conclusion

Response monitoring is a key mechanism in human cognition and occurs on multiple levels: On an inter-individual level, it differs *between* individuals; on an intra-individual level, it varies *within* individuals. In this thesis, I have illustrated the utility of studying response monitoring on both levels. Investigating how different dimensions and types of perfectionism differ in response monitoring allows to identify latent mechanisms in perfectionists that contribute to the emergence of observable perfectionistic behaviour. Investigating how response monitoring is linked to post-response adaptation on a trial-by-trial basis advances our knowledge about how the cognitive system implements adaptive measures in an effort to perform in accordance with task requirements. Future research may benefit from integrating both levels of response monitoring and from employing and combining more sophisticated methods like single-trial ERP analyses and diffusion model analyses to gain more detailed insights into response monitoring and related processes.

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Author contributions

In the following, the authors' contribution to the two studies presented in this thesis are listed using the Contributor Roles Taxonomy (CRediT) system.

Study 1

André Mattes: Conceptualization, Data curation, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Markus Mück**: Validation, Writing – review & editing. **Jutta Stahl**: Conceptualization, Validation, Resources, Data curation, Writing – review & editing, Supervision, Funding acquisition.

Study 2

André Mattes: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Elisa Porth**: Validation, Methodology, Writing – review & editing. **Jutta Stahl**: Conceptualization, Methodology, Validation, Resources, Data curation, Writing – review & editing, Supervision, Funding acquisition.

Appendix

The current thesis is based on two studies. Both studies have been published in peer-reviewed journals. The published versions of these studies are provided below.

Study 1

Mattes, A., Mück, M., & Stahl, J. (2023). Perfectionism-related variations in error processing in a task with increased response selection complexity. *Personality Neuroscience*, *5*, e12. https://doi.org/10.1017/pen.2022.3

Study 2

Mattes, A., Porth, E., & Stahl, J. (2022). Linking Neurophysiological Processes of Action Monitoring to Post-Response Speed-Accuracy Adjustments in a Neuro-Cognitive Diffusion Model. *NeuroImage*, *247*, Article 118798. https://doi.org/10.1016/j.neuroimage.2021.118798