BERGISCHE
UNIVERSITÄT
WUPPERTAL

Dissertation im
Fach Psychologie
mit dem Titel

Feedback-Induced Learning in Aging Minds: Neural and Behavioral Adaptation to Socio-Emotional Feedback

zur Erlangung des akademischen Grades
Doctor rerum naturalium (Dr. rer. nat.)

durch die Fakultät für Human-
und Sozialwissenschaften
der Bergischen Universität Wuppertal

vorgelegt von Jana Isabelle Braunwarth
aus Bochum

Bochum, im März 2026

Acknowledgments

I would like to thank the many people without whom this dissertation would not have been possible. First and foremost, I am deeply indebted to my doctoral supervisor, Professor Nicola Kristina Ferdinand, for her guidance, unwavering support, and invaluable advice throughout this journey. Her trust, encouragement, and patience not only made this dissertation possible but also allowed me to grow both academically and personally. I am also sincerely grateful to Dr. Corinna Lorenz for her continuous support and exchange, both professional and beyond, as well as to my colleagues Anna Theresa Kläser and Johannes Levin Graf for always being ready for a good conversation about life when it was most needed. I further wish to thank Dr. Daniela Pfabigan for her valuable input, collaboration, and expertise. Special thanks go to all study participants, whose willingness to contribute their time and effort made this dissertation possible in the first place, as well as to all the students who worked with me on the various projects.

On a more personal note, I am profoundly thankful to my family, especially my niece Effie, for being a delightful and invaluable distraction, and to my friends for their constant support, even when I repeatedly declined invitations and promised to reschedule “soon”. I would also like to thank Prof. Dr. Dominik Rumlich and Dr. Johannes Jungilligens for their motivational talks, especially toward the end of this journey. I owe my deepest gratitude to Stephan for his unconditional support, for lifting my spirits with laughter, and for gently reminding me to step away from my desk and enjoy life along the way. Finally, I would like to thank the little one on the way, who joined me during the final stage of this dissertation and has already made this journey even more memorable.

Abstract

In an aging society, understanding age-related differences in learning is crucial for supporting older adults' active participation in everyday life. Previous research suggests that socio-emotional feedback, such as facial expressions, may facilitate learning in older adults, potentially reflecting motivational shifts or compensatory neural mechanisms. However, it remains unclear whether these benefits reflect developmental changes in older age or also increased cognitive demands in younger adults due to working memory limitations. Moreover, socio-emotional feedback comprises multiple facets; emotionality, sociality, and communicative meaning and it remains debated which of these drive learning benefits.

Across three studies using a probabilistic learning task, (1) working memory capacity, (2) emotional intensity, and (3) the sociality of feedback stimuli were systematically manipulated. Neural mechanisms underlying feedback processing were investigated using event-related potentials (ERPs), focusing on the feedback-related negativity (FRN), associated with the detection of unexpected events, and the P3b, reflecting the updating of working memory representations. Study 1 manipulated working memory load in younger adults while comparing socio-emotional (faces) with non-emotional (scrambled faces) feedback. Socio-emotional feedback facilitated learning and enhanced neural processing largely independent of working memory capacity, motivating for a more precise stimulus control in subsequent studies. Study 2 therefore examined the role of emotional intensity by comparing weak and strong facial expressions as feedback in younger and older adults. Both groups learned better after strong emotional feedback, but older adults showed a stronger benefit. Neural results further indicated that younger adults primarily relied on feedback valence for working memory updating, whereas older adults additionally integrated emotional intensity. Study 3 isolated the social component of

feedback by comparing social (unfamiliar hand gestures) with non-social (abstract shapes) stimuli. Both age groups learned better from social feedback, with older adults again showing greater benefits. Neural responses revealed age-specific patterns in the detection of unexpected events, while social feedback generally enhanced working memory updating across groups. The present dissertation extends findings that socio-emotional feedback supports learning via multiple, partially dissociable mechanisms that differ across the adult lifespan. The results suggest that learning benefits from socio-emotional feedback in older adults are not solely attributable to increased working memory demand, but may reflect a biologically grounded processing advantage, which is strengthened by motivational shifts. Together, these findings advance current accounts of motivational and compensatory mechanisms in neurocognitive aging and recommend the targeted use of socio-emotional feedback in more applied contexts such as digital learning interventions for older adults.

Zusammenfassung

Im Zuge des demographischen Wandels ist das Verständnis altersbedingter Lernunterschiede zentral für die aktive Teilhabe älterer Menschen. Frühere Forschung legt nahe, dass sozio-emotionales Feedback, etwa durch Gesichtsausdrücke, das Lernen bei älteren Erwachsenen erleichtern kann. Dies könnte auf motivationale Veränderungen im Alter oder kompensatorische neuronale Mechanismen zurückzuführen sein. Unklar ist jedoch, ob diese Vorteile entwicklungsbedingte Veränderungen im höheren Lebensalter widerspiegeln oder auf erhöhte kognitive Anforderungen infolge begrenzter Arbeitsgedächtniskapazität zurückgehen. Zudem umfasst sozio-emotionales Feedback mehrere Dimensionen: Emotionalität, Sozialität und kommunikative Bedeutung, und es ist bislang unklar, welche davon den beobachteten Lernvorteilen zugrunde liegen.

In drei Studien mit einer probabilistischen Lernaufgabe wurden (1) die Arbeitsgedächtniskapazität, (2) die emotionale Intensität sowie (3) die Sozialität der Feedbackstimuli systematisch variiert. Die neuronalen Mechanismen der Feedbackverarbeitung wurden mithilfe ereigniskorrelierter Potenziale untersucht. Der Fokus lag dabei auf der feedbackbezogenen Negativität, die mit der Detektion unerwarteter Ereignisse assoziiert ist, sowie auf der P3b-Komponente, die die Aktualisierung von Arbeitsgedächtnisrepräsentationen widerspiegelt.

In Studie 1 wurde bei jüngeren Erwachsenen die Arbeitsgedächtniskapazität manipuliert, während sozio-emotionales Feedback (Gesichter) mit nicht-emotionalem Feedback (fragmentierte Gesichter) verglichen wurde. Sozio-emotionales Feedback erleichterte das Lernen und verstärkte die neuronale Verarbeitung weitgehend unabhängig von der Arbeitsgedächtniskapazität. Dies

führte zu einer präziseren Kontrolle der Stimulusmerkmale in den folgenden Studien. Studie 2 untersuchte daher die Rolle der emotionalen Intensität, indem schwache und starke Gesichtsausdrücke als Feedback bei jüngeren und älteren Erwachsenen verglichen wurden. Beide Gruppen lernten besser nach stark emotionalem Feedback, wobei ältere Erwachsene einen größeren Lernvorteil zeigten. Die neuronalen Ergebnisse zeigten zudem, dass jüngere Erwachsene beim Aktualisieren von Arbeitsgedächtnisinformationen vor allem auf die Valenz des Feedbacks zurückgriffen, während ältere Erwachsene zusätzlich die emotionale Intensität integrierten. Studie 3 isolierte die soziale Komponente sozio-emotionalen Feedbacks, indem soziale (unbekannte Handgesten) mit nicht-sozialen (abstrakte Formen) Stimuli verglichen wurden. Beide Altersgruppen lernten besser aus sozialem Feedback, wobei ältere Erwachsene erneut größere Vorteile zeigten. Die neuronalen Reaktionen wiesen altersspezifische Muster bei der Detektion unerwarteter Ereignisse auf, während soziales Feedback insgesamt die Aktualisierung von Arbeitsgedächtnisinformationen erleichterte.

Die vorliegende Dissertation erweitert bestehende Befunde, indem sie zeigt, dass sozio-emotionales Feedback das Lernen über unabhängige Mechanismen unterstützt, welche sich über die Lebensspanne hinweg unterscheiden. Die Ergebnisse legen nahe, dass Lernvorteile durch sozio-emotionales Feedback bei älteren Erwachsenen nicht ausschließlich auf erhöhte Anforderungen an das Arbeitsgedächtnis zurückzuführen sind, sondern auch einen biologisch begründeten Verarbeitungsvorteil widerspiegeln könnten. Dieser scheint zudem durch motivationale Veränderungen verstärkt zu werden. Insgesamt tragen die Befunde zu einem besseren Verständnis motivationaler und kompensatorischer Mechanismen während des Alterns bei und sprechen für den gezielten Einsatz sozio-emotionalen Feedbacks, zum Beispiel in digitalen Lerninterventionen.

Contents

List of figures

List of tables

Abbreviations

ACC — Anterior cingulate cortex

DA — Dopamine

DLPFC — Dorsolateral prefrontal cortex

EEG — Electroencephalography

ERP — Event-Related Potential

FRN — Feedback-Related Negativity

ERN — Error-Related Negativity

fMRI — Functional Magnetic Resonance Imaging

SN — Substantia Nigra

SST — Socioemotional Selectivity Theory

SAVI — Strength and Vulnerability Integration Model

VTA — Ventral tegmental area

MPFC — Medial prefrontal cortex

RewP — Reward Positivity

RL — Reinforcement Learning

RPE — Reward Prediction Error

TD error — Temporal difference error

VMPFC — Ventromedial Prefrontal Cortex

1 General introduction

From our earliest years, learning through feedback shapes how we navigate the world. As children, we discover that crying may sometimes bring a cookie, but not always. In school, we learn that shouting in class seldom pays off. At university, we find that midnight coffee can buy a few hours of alertness, but at the expense of the next morning. In adulthood, we learn that filing taxes brings no joy but spares us greater pain. And by older age, learning often means trying to remember which button opens the ticket app, which password still works, and why yesterday's solution no longer applies after a software update. What begins as a series of everyday behavioral adjustments across the lifespan reflects a fundamental mechanism: the ability to learn from feedback. In light of ongoing demographic shifts in the global population, marked by increased longevity and declining birth rates, understanding how feedback-induced learning evolves and adapts in later life has become increasingly relevant.

While some structural changes, such as reduced dopamine receptor density and firing activity, are well established to lead to cognitive changes in aging (Fjell & Walhovd, 2010; Lee & Kim, 2022), certain processes appear to remain relatively stable or do even improve (Mather, 2012). Some of these processes rely on the preservation of brain areas, involved in affective processes, such as the amygdala and the limbic system (Leclerc & Kensinger, 2008). In addition to the relationship with these brain structures, motivational aging theories suggest that older adults focus more on emotional well-being and stable social relationships (Carstensen, 1991; Charles, 2010). These theoretical concepts raise important questions about how older adults may benefit especially from social or emotional information during learning and how this type of feedback is processed throughout life. Revisiting the aforementioned example of navigating a ticket application

illustrates how age-related reductions in dopaminergic functioning and processing efficiency may translate into everyday learning challenges. However, when feedback in these contexts is socially embedded, for example, through interpersonal explanations, guidance, or emotionally meaningful stimuli, it may be processed more effectively by older adults and thereby acting possibly as a compensation.

These learning processes involve, first, realizing that a familiar routine no longer works as expected, such as when opening a ticket app and noticing that the usual button no longer appears in the same place after a software update, thereby experiencing an expectancy violation, and second, keeping the new information in mind (for instance, remembering which option now leads to the ticket purchase or which password still works) to adapt future behavior. Similar challenges may also arise in younger adults when working memory load is high, for example, when several steps must be remembered simultaneously while navigating the application. Evidence for a potential benefit of socio-emotional feedback during learning in younger and older adults is, however, to date limited and inconsistent, underlining the necessity to further elaborate this topic (Ferdinand & Hilz, 2020; Nashiro et al., 2011; Pfabigan et al., 2019; Pfabigan & Han, 2019). Socio-emotional feedback, such as an emotional facial expression or a simple social signal like a “thumbs up”, may serve as a relevant stimulus that reinforces which option to select the next time when navigating the ticket app after a software update. While older adults may particularly benefit from such external signals, younger adults might only rely on them when working memory resources are strained (Ferdinand & Hilz, 2020).

The present doctoral thesis therefore investigates whether cognitive capacity in working memory is needed to benefit from socio-emotional feedback in younger adults to show similar learning and processing advantages as older adults, followed by which characteristics, sociality,

emotionality or communicative meaning of socio-emotional feedback lead to those learning benefits , especially in older adults.

By combining behavioral measures with feedback-related ERPs, the present work contributes to current theoretical models and empirical research on age-related learning processes. It seeks to further specify how feedback is processed across the lifespan and to provide a more differentiated account of the mechanisms underlying adaptive learning in older adults. Beyond advancing theoretical understanding, these findings may also have implications for applied contexts. A more precise characterization of feedback processing in aging could inform the development of cognitive training approaches, behavioral interventions, or digital learning tools. In the longer term, such insights may help to support adaptive functioning and sustained participation in social and professional domains among older adults.

1.1 Theoretical foundations of feedback-induced learning

The ability to flexibly adapt behavior in response to changing environmental demands is a central part of human cognition. Already in the early 1900s, Thorndike (1911) stated that the probability to show a specific behavior increases after receiving favorable in comparison to non-favorable outcomes. Thorndike (1911) called this the “law of effect”, meaning that a specific type of behavior would be shown more when it resulted in positive consequences and that behavior, which is followed by a negative consequence, will be shown less. In his work on operant conditioning, Skinner (1963) used the similar approach to develop a learning theory, stating that a specific response to a stimulus is strengthened by reward or punishment (Skinner, 1963). By this, the basis for reinforcement learning (RL) models was set. Building on these classical accounts, contemporary frameworks emphasize that adaptive behavior requires continuous performance

monitoring and flexible updating of ongoing behavior in light of the current goals (Ullsperger, 2024). During behavioral adaptation, performance needs to be monitored and flexibility is required to determine when behavior should be adjusted. Future decisions are influenced by these processes and are supported by feedback that either aligns with these goals or provides the information necessary for behavioral adjustment in order to achieve them. Such adjustments draw on a broad set of mechanisms, including automatic responses, such as the detection of errors, or cognitive control processes (e.g., heightened alertness, or attention), and shifts in affect and motivation. Together, these performance monitoring operations support wide-ranging and flexible adaptations that are summarized by the feedback evaluation-adaptation loop, developed by Ullsperger (2024) (see Figure 1.2 for more details).

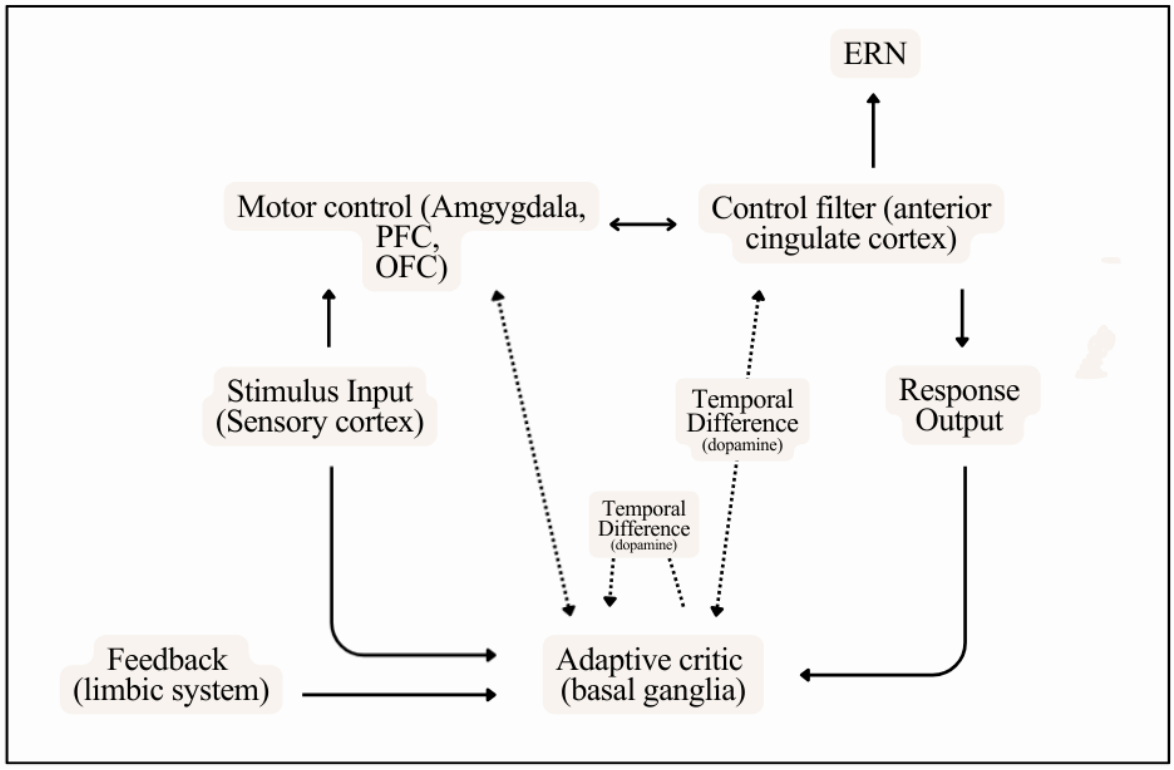
Early animal research has provided important insights into how learning from feedback leads to adaptive behavior and is represented at the neural level. Influential work by Schultz (1986) demonstrated that dopaminergic (DA) neuron activity in monkeys encodes a reward prediction error (RPE) rather than merely responding to reward delivery. Neurons within the ventral tegmental area (VTA) and substantia nigra (SN) exhibit increased firing in response to unexpected rewards, with this activity shifting to the predictive stimulus once the reward becomes expected. Structurally, the VTA is a diffuse ventromedial midbrain complex organized into loosely defined subnuclei. The SN is a mesencephalic basal ganglia structure composed of the pars compacta, which is involved in DA synthesis and therefore important for the neural processing of learning from feedback, and the pars reticulata, which predominantly contains gamma-aminobutyric acid (GABA)–ergic neurons. If an expected reward fails to occur, dopaminergic firing is reduced. The reduced firing reflects a mismatch between expected and actual outcomes and offers a neural mechanism through which the brain updates reward expectations and adjusts subsequent behavior

due to reward prediction errors (Schultz, 1986; Schultz, 2002). Accordingly, expectations and violations of expectations constitute fundamental principles underlying learning from feedback and adaptive behavior.

Holroyd and Coles (2002) used these findings to investigate human error processing by developing the RL-Error-related negativity (ERN) theory. This RL-ERN theory offers a computational framework, describing how the brain evaluates performance to adapt behavior. The model centers on the computation of a temporal difference (TD) error, encoded by mesencephalic dopaminergic neurons and signaled to the medial prefrontal cortex (mPFC), specifically the anterior cingulate cortex (ACC). When outcomes deviate from expectations, phasic increases or decreases in dopaminergic activity signal positive or negative TD errors, respectively. These dopaminergic signals modulate activity within the ACC, enabling it to learn which control systems or action strategies are the most effective motor controllers in a given context. Across trials, eligibility traces temporarily mark recently active neural pathways, allowing later reinforcement signals to intensify these pathways and eventually strengthen learning. The presented model provides an excellent theoretical overview on how behavior is adapted based on reinforcement learning. Thereby, the described dopaminergic phasic decreases and increases in response to prediction errors are shown to be reflected in ERPs. ERPs measured with the EEG are a non-invasive method to measure scalp potential fluctuations. Because of its high temporal resolution, it is especially useful for investigating cognitive processes during feedback-induced learning. ERPs reflect rapid, time-locked changes in the brain's electrophysiological activity that arise in response to specific internal or external events. They provide millisecond-level insights into perceptual, motor, and cognitive processes (Luck & Kappenmann, 2012).

Figure 1.1

Reinforcement Learning-ERN Theory



Note. Neurocognitive framework of feedback-induced action control, depicting information through the ACC and feedback-induced learning via basal ganglia and dopaminergic teaching signals (adapted from Holroyd & Coles, 2002).

1.1.1 Neural indices of performance monitoring

ERPs linked to performance monitoring can be measured at multiple time points. The ERN, for example, is an early negative going signal around 50-100ms occurring during an incorrect response and is assumed to be mainly generated in the ACC with its maximum at fronto-central areas (Falkenstein et al., 1990; Gehring et al., 1993; Miltner et al., 1997). The feedback-related negativity (FRN), also called medial-frontal negativity or feedback negativity (Gehring &

Willoughby, 2002; Miltner et al., 1997), in contrast, is a negative waveform in a time window at around 200-300ms after feedback (receiving external input) has been presented at primarily fronto-central (at FCz or Fz) areas (Holroyd & Coles, 2002; Miltner et al., 1997). According to reinforcement learning accounts, the FRN is elicited by outcomes that are evaluated as worse than expected, reflecting a dopaminergically mediated prediction error signal that modulates activity in the ACC. During the learning process, negative feedback becomes more unexpected, which according to the assumption of Holroyd and Coles (2002) leads to an enlarged FRN and thereby indicating a signed RPE. This assumption gained popularity and has been supported across a wide range of feedback processing studies (Borries et al., 2013; Eppinger et al., 2008; Frank et al., 2005; Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Holroyd & Krigolson, 2007; Meel & Heijningen, 2010; Miltner et al., 1997; Nieuwenhuis et al., 2004; Opitz et al., 2011), suggesting that activation in the FRN eventually leads to behavioral adaptation and better performance (Cohen & Ranganath, 2007; Walsh & Anderson, 2012; Wild-Wall et al., 2009).

In recent years, an alternative interpretation of this feedback-related time window has attracted increasing attention. The reward positivity (RewP) is characterized as a positive deflection emerging approximately 250 ms after feedback onset and peaking at a scalp site comparable to that of the FRN. It is primarily elicited by outcomes that are better than expected and is thought to originate in the ACC. Findings from this body of research indicate that reward processing may be prioritized over the processing of losses (Holroyd et al., 2008a; Proudfit, 2015). Due to the substantial overlap in both temporal dynamics and neural generators, there is an ongoing debate concerning the functional differentiation of these ERPs (Sambrook & Goslin, 2014; Walsh & Anderson, 2012).

Another model, the Predicted Response–Outcome (PRO) model by Alexander and Brown (2011), provides a complementary perspective on this debate, proposing that the mPFC, including the ACC, actively generates predictions about the outcomes of actions based on previous outcomes and signals, when these predictions are violated. Unlike models, in which the mPFC functions as a passive recipient of dopaminergic feedback (such as in the RL-ERN Theory), the PRO model suggests that the mPFC adapts associations between responses and their expected outcomes, integrating information regarding the probability, magnitude, and timing of those outcomes (Alexander & Brown, 2011, 2019; Brown & Alexander, 2017). When an expected event fails to occur, or when an unpredicted outcome results from the action, the mPFC produces a prediction error proportional to the discrepancy between expected and actual outcome. The PRO model therefore provides a coherent account of mPFC activity not only during feedback-induced learning, but also in contexts involving surprise, novelty, or cognitive conflict, thereby redefining the role of the mPFC as a predictive monitoring system (Alexander & Brown, 2011, 2019; Brown & Alexander, 2017; Hauser et al., 2014; Paul et al., 2025; Vassena et al., 2020).

From this perspective, learning from feedback, responding to surprising events, and adjusting all stem from a common computational process, the evaluation of how actual outcomes differ from expectations, here called expectancy violations. Accordingly, FRN learning studies offer compelling converging evidence that the mPFC, especially the ACC, is sensitive to these predictive deviations during ongoing behavior due to surprising signals, positioning the FRN within a broader framework of performance monitoring and reflecting the participants' detection of unexpected events, thereby representing an unsigned RPE (Bellebaum & Daum, 2008; Ferdinand et al., 2012; Hauser et al., 2014; Oliveira et al., 2007; Paul et al., 2025; Pfabigan et al., 2011).

Although both models are based on the premise that learning is driven by mismatches between expected and actual outcomes, they place differential emphasis on distinct dimensions of performance monitoring. Whereas the RL-ERN theory primarily highlights outcome valence, the PRO model highlights outcome expectedness irrespective of valence. These conceptual differences are further reflected in differing accounts of medial prefrontal cortex involvement. In the reinforcement learning account, the mPFC is conceptualized primarily as a recipient of dopaminergic prediction error signals, whereas the PRO model attributes an active role in learning response–outcome associations to prefrontal region. These mechanistic distinctions are not critical for the aims of the present thesis, as both frameworks converge on the use of the FRN as a neural marker for negative expectancy violations and early outcome detection. Accordingly, this thesis focuses on the FRN as an index of early feedback processing, while acknowledging that this signal may be driven by unexpectedness and valence.

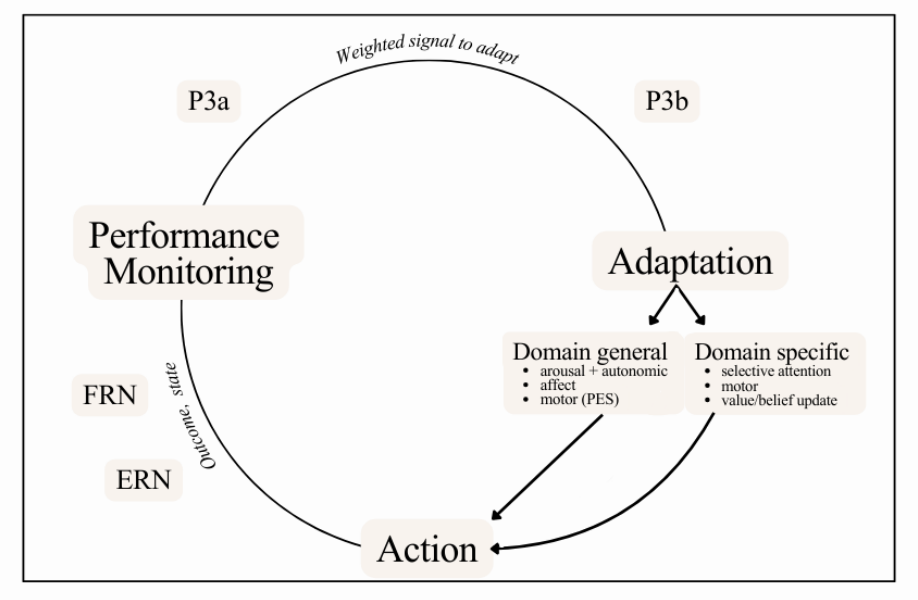
So far, theoretical models, reflecting performance monitoring processes and their associated ERP components, have been introduced. These processes highlight the detection of unexpected events during feedback-induced learning. Although these early neural responses can, in some cases, lead to later behavioral adjustments, they do not necessarily do so and may instead reflect an initial detection of feedback outcomes (Pfabigan et al., 2011; Walsh & Anderson, 2012). This suggests that early detection represents only one step within a broader cascade of neural processes and raises the question of which mechanisms underlie the transition from outcome detection to behavioral adaptation accordingly.

This distinction is addressed in the feedback evaluation - adaptation loop proposed by Ullsperger (2024). In this framework, performance monitoring constitutes one stage within a broader behavioral adaptive process. During this process, it is evaluated whether a decision has

produced the desired outcome. Based on this evaluation, feedback-induced learning updates expectations and beliefs, which then shape future decision making as well as subsequent performance monitoring. However, errors can still occur, which requires continued flexibility and behavioral adaptation. These adjustments can use multiple mechanisms, by which the adaptation is performed. Performance monitoring, thus, converts evaluated performance information into an internal signal that specifies whether behavioral adaptation is needed, in order to correct current errors or improve future behavior (see Figure 1.2).

Figure 1.2

Conceptual model for feedback evaluation and adaptation



Note. Model linking feedback-induced performance monitoring to adaptive behavior via the ERN/FRN, P3a, and P3b components (adapted from Ullsperger, 2024).

1.1.2 Neural indices of context updating

Between performance monitoring and subsequent behavioral adaptation, an intermediate stage can be assumed in which the current context representation is brought up to date based on the most recent feedback. This process is closely linked to mechanisms of working memory updating and is theoretically grounded in the context updating hypothesis (Donchin & Coles, 1988; Polich, 2004, 2007; Polich & Criado, 2006; Sutton et al., 1965). This hypothesis describes the cognitive and neurophysiological mechanisms underlying the P300 component, a positive-going ERP occurring approximately 300–600 ms after stimulus onset (Polich, 2007). It has been traditionally investigated by using Oddball paradigms. These paradigms involve the presentation of

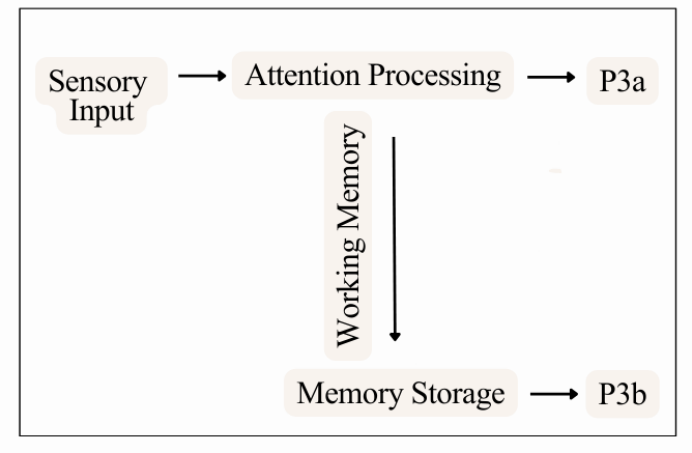
predominantly similar stimuli interspersed with rare, feature-deviant or contextually distinct events, which are used to investigate neural processing of unexpected or novel stimuli (Debener et al., 2005; McCarthy & Donchin, 1981). When a stimulus deviates from the current cognitive framework or task context, the brain initiates a comparison mechanism that results in an updating process, manifested as the P300 component (Donchin & Coles, 1988). If it does match, other sensory evoked potentials are shown. These representations have been additionally shown to be influenced by attentional resources or capacity, thereby studies frequently showed that the P300 is smaller when attentional capacity reached its limit (Kok, 2001; Polich, 1987). The P300 reflects a family of positive ERPs arising from distributed cortical networks. Lesion and neuroimaging studies have on one hand localized the P3a predominantly to frontal regions, including the medial prefrontal cortex and ACC, where it has been associated with attentional orienting toward novel stimuli. On the other hand, the P3b has been linked primarily to posterior parietal regions and is thought to reflect processes related to context updating and working memory (Kirino et al., 2000; Polich, 2007; Polich & Criado, 2006). Together, these processes show a dynamic interplay between attention allocation, memory updating, and behavioral adaptation (see Figure 1.3 for graphical illustration) (Conroy & Polich, 2007).

In the context of learning from feedback, several studies examined the effects by which the P3b could be manipulated. As such, probability, outcome magnitude, and task structure were shown to critically determine P3b amplitude, as well as task-relevant information for achieving the goal, which signals the need for behavioral adjustment (Ferdinand, 2019; Ferdinand & Czernochowski, 2018; Polich, 2007; Sato et al., 2005; Yeung et al., 2004, 2005). Regarding probability, studies revealed that the P3b is larger for unexpected than expected feedback and more pronounced for larger magnitudes of feedback in contrast to smaller ones (see San Martín, 2012

for a review). Further, negative feedback valence also affected the P3b amplitude in recent research (Ferdinand, 2019; Frank et al., 2005; Kamp et al., 2024). In addition, increased task demands have been shown to reduce P3b amplitudes, consistent with the notion of limited processing capacity and working memory updating (Donchin & Coles, 1988; Kok, 2001; Polich, 2007). Conversely, more infrequent stimuli reliably elicit larger P3b amplitudes, reflecting greater context updating demands in feedback-induced learning paradigms (Martín, 2012; Sato et al., 2005).

Figure 1.3

Functional distinction between P3a and P3b



Note. Schematic illustration of the proposed functional distinction between P3a and P3b in attentional processing of novel stimuli and working memory updating (adapted from Polich, 2007).

In the present chapter, the theoretical foundations of feedback-induced learning and its neural substrates were reviewed. Two complementary frameworks central to the interpretation of feedback-related neural activity, expectancy violation and working-memory context updating, were described, with the FRN linked to expectancy violation and the P3b indexing context updating. These considerations form the conceptual and neurophysiological basis for the empirical investigations presented in the subsequent chapters and give an explanation on why aging processes can affect learning from feedback.

1.2 The aging brain

Aging is accompanied by structural and neurochemical changes, which interfere with neural systems associated with feedback-induced learning and thus may lead to reductions in processes involved in feedback learning. In the following chapter, these changes are described and a theoretical model will be introduced to explain these age-related differences.

1.2.1 Structural changes

During aging, our brain undergoes several structural changes; among them gray matter loss, which is a tissue in the brain as well as in the spinal cord, containing clusters of neurons, cell bodies, dendrites and axon terminals (see Kennedy & Raz, 2015 for a review). Gray matter volume decreases gradually across the lifespan beginning in early to mid-adulthood, with evidence suggesting that this decline becomes more pronounced in later life (Fjell et al., 2014). Importantly, this reduction does not occur uniformly across the brain, as some regions appear to be affected earlier than others (Kennedy & Raz, 2015; Lee & Kim, 2022; Lemaître et al., 2012; Raz & Rodrigue, 2006). The early-affected brain regions have been shown to be especially within prefrontal regions, such as the dorsolateral prefrontal cortex (DLPFC), the ACC, the inferior frontal

gyrus as well as the insula (Dempster, 1992; Giorgio et al., 2010; Neufeld et al., 2022; Sullivan et al., 1995; West, 1996). In contrast, MRI studies have shown that gray matter in limbic structures, such as the amygdala and hippocampal areas, is less prone to decline with healthy aging (Farokhian et al., 2017; Grieve et al., 2005). This proneness to age-related decline in gray matter is assumed to be primarily driven through dendritic reductions and synaptic shrinkage (Fjell & Walhovd, 2010). Further, aging has been linked to a reduction in white matter. White matter, the tissue primarily found in subcortical areas and covered by myelin, has also been shown to decline during aging, with a later onset than gray matter (Alexander et al., 2006; Fjell et al., 2014; Raz & Rodrigue, 2006; Walhovd et al., 2005). White matter plays a crucial role in enabling efficient communication between distributed gray matter regions, as it supports the transmission and precise temporal coordination of neural signals along myelinated axonal pathways. With increasing age, alterations in myelin integrity and axonal organization affect these pathways and may consequently reduce the efficiency of interregional neural communication (Bethlehem et al., 2022; Groh & Simons, 2025).

1.2.2 Dopaminergic alterations

Healthy aging is associated not only with macroscopic structural brain changes and global atrophy, but also with systematic modifications of the brain's neurochemical environment, which has important implications for the efficiency, flexibility, and stability of neural information processing. As described in Chapter 1.1, DA neurotransmission plays a key role in feedback-induced learning. Therefore, the present section focuses specifically on age-related changes within the DA system.

DA is a catecholamine, which functions as a neuromodulator and neurotransmitter in the central nervous system. It is synthesized from tyrosine through tyrosine hydroxylase to L-DOPA and through aromatic amino acid decarboxylase to dopamine. It is primarily produced in the VTA and SN pars compacta (Katolikova & Gainetdinov, 2021). It also functions as a precursor for norepinephrine and epinephrine. There are four primary dopaminergic pathways: the nigrostriatal, the mesolimbic, the mesocortical, and the tuberoinfundibular pathway (Harsing, 2008). The mesolimbic and mesocortical pathway are those specifically linked to feedback-induced learning. The mesocortical pathway originates in the VTA and projects to the prefrontal cortex. In contrast, the mesolimbic pathway links the VTA with the ventral striatum, including the nucleus accumbens and the olfactory tubercle. Functionally, the two pathways differ in their primary contributions. The mesolimbic pathway encodes motivational salience and reinforcement processes, whereas the mesocortical pathway supports the cognitive evaluation and regulation of these motivational signals and integrates them into goal-directed behavior.

Given the central role of DA in both pathways, age-related differences in the DA system may have widespread functional consequences. Indeed, studies have shown that DA levels decline by approximately 10% per decade with increasing age (Bäckman et al., 2000; Karrer et al., 2017; Volkow et al., 1996). A large body of empirical evidence indicates that healthy aging is accompanied by changes at multiple levels of dopaminergic signaling. Neuroimaging studies consistently demonstrate age-related reductions in several dopaminergic markers, including the availability of DA receptors, dopamine transporters, and indices of dopamine synthesis and release. These effects are particularly pronounced in striatal regions such as the putamen and caudate nucleus, as well as in prefrontal cortical areas (Bäckman et al., 2000; Bäckman et al., 2010; Karrer et al., 2017; Li & Rieckmann, 2014; Volkow et al., 1996). According to the well-documented age-

related alterations in the dopaminergic system and the critical involvement of dopamine in feedback-induced learning, a significant decrease in learning efficiency from feedback is assumed with age.

1.2.3 Age-related changes in feedback-induced learning

As outlined in Chapter 1.1, feedback-induced learning, including the detection of unexpected outcomes and the updating of working memory based on feedback, critically depends on DA signaling, which is affected during aging. Importantly, age-related changes in DA function do not manifest as a uniform global decline, but rather as subtle alterations affecting specific aspects of DA release, and receptor availability. Against this background, it remains unclear how these differences in DA modulation are reflected in cognitive performance patterns across the adult lifespan.

A model proposed by Braver and Barch (2002) offers such a neuromodulatory account of these changes, highlighting age-related reductions in the maintenance and updating of context representations. The model assumes that successful performance depends on the active maintenance and flexible updating of an internal context representation that supports adaptive behavior. Here, “context” refers broadly to any task-relevant stimulus or intended action. Such representations become especially critical when behavior requires choosing between correct and incorrect responses, making their active maintenance in working memory essential.

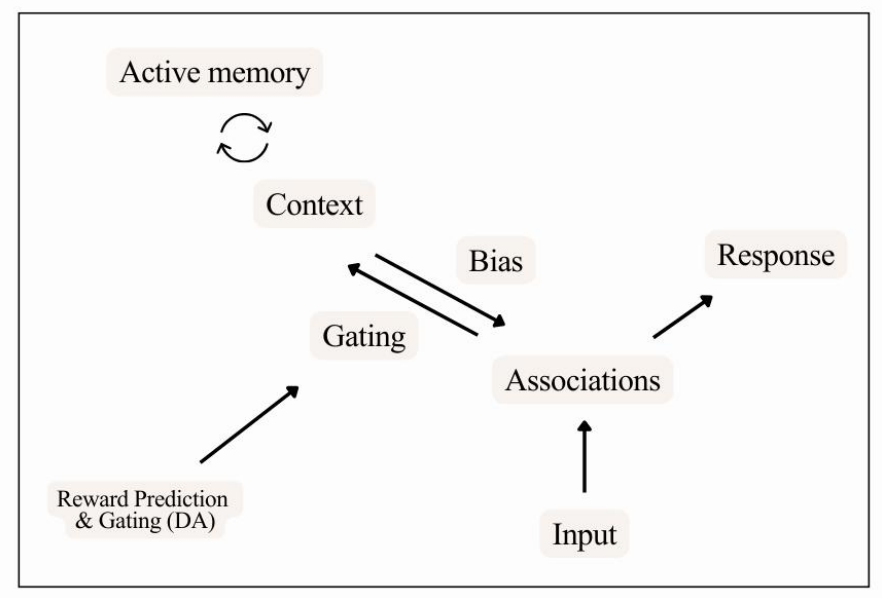
In this model, context representations are maintained and adjusted in the DLPFC, supported by DA projections that regulate both stability and flexibility. Incoming information initially enters the system as external input and is processed within an associative layer that stores learned mappings between stimuli and actions. Specifically, this means that already known associations of

the input support this processing. The PFC then acts as an active memory system that sustains context information guiding current behavior. This active context biases downstream processing by selectively emphasizing information relevant to the current goals, allowing the system to focus on what matters at a given moment.

A central component of the presented model regarding the context updating in working memory is the DA-dependent gating mechanism that determines which incoming information is permitted to update the currently active context. Not all information is treated equally; only stimuli, perceived behaviorally relevant are allowed through the gate. DA activity then plays a critical role by signaling whether events are rewarding or unexpected. Surprise, unexpectedness, and reward trigger phasic DA release, effectively opening the gate and enabling the PFC to update its working memory with new context representations. When incoming information lacks relevance or reward value, the gate remains closed and existing representations are preserved. Braver and Barch (2002) therefore argue that DA supports both the reward prediction and the maintenance of context through distinct neural pathways. They further proposed that age-related differences in DA transmission may serve as a common mechanism underlying a wide range of cognitive deficits. Their central aging assumption is that due to reduced dopaminergic activation, the gate opens less effectively and less often. As a result, aging is accompanied by poorer context updating and instability, which then leads to more errors and slower adaptation through reduced working memory processes. The model does not posit that older adults in general learn worse and slower, with effects on detecting unexpected events or working memory updating, but rather in situations that depend on the active maintenance of task goals.

Figure 1.4

Cognitive control model illustrating DA dependent gating mechanism



Note. This illustration was adapted from Braver & Barch, 2002.

There is ample evidence that age-related DA changes primarily affect executive functions, working memory, but also learning ability, and processing speed (Gajewski et al., 2018; Guerrero et al., 2022; Mell et al., 2005; Nagel et al., 2009; Reuter-Lorenz et al., 2000). Baltes and Lindenberger (1999) propose that age-related decline in these processes reflects reductions in mechanics abilities, particularly processing speed, but also age-related changes in sensory functions such as vision and hearing. In contrast, other, more pragmatic cognitive abilities, as described by Baltes and Lindenberger (1999), such as crystallized intelligence and vocabulary, are assumed to remain stable or even improve in older adulthood (Salthouse, 2010). These assumptions suggest that age-related neurochemical changes, including alterations in DA signaling, may disproportionately affect cognitive functions that rely on flexible updating, learning from feedback, and rapid adaptation, rather than cognitive performance per se.

On a behavioral level, learning studies almost consistently show that older adults are less accurate and slower than younger adults (Ferdinand, 2019; Hämmerer et al., 2011; Mathewson et al., 2008; Mell et al., 2005; Pietschmann et al., 2008; Wild-Wall et al., 2009). While Mell et al. (2005) used a probabilistic object reversal task and Mathewson et al. (2008) a spatial learning task, Pietschmann et al.(2008, 2011) used a probabilistic learning task to investigate behavioral as well as neurophysiological performance and improvements of learning in older adults across time. Building on this, it should be noted that various methodological approaches can be used to examine age-related learning deficits. Whereas probabilistic object reversal tasks assess learning flexibility and the ability to adapt to changing contingencies, and spatial learning tasks primarily tap into spatial memory processes with deterministic output, probabilistic learning tasks are particularly suited to examine feedback-induced learning. Probabilistic learning tasks selectively assess feedback-induced adaptation to probabilistic outcomes, capturing feedback detection and updating while minimizing additional demands on inhibition and rule-switching processes that characterize many executive control tasks. In addition, age-related differences in probabilistic learning performance are consistent with dopamine (DA) modulation. These differences can be effectively assessed using neural indices of performance monitoring (reflected in the FRN) and working memory updating (reflected in the P3b), rather than relying solely on behavioral measures (Ferdinand & Czernochowski, 2018; Gajewski et al., 2018; Gorlick et al., 2013).

In many of the probabilistic learning studies, older adults showed markedly reduced FRN amplitudes compared to younger adults (Eppinger et al., 2008; Hämmerer et al., 2011; Nieuwenhuis et al., 2002; Pietschmann et al., 2008), which may correspond to the reduced DA activity and explain the diminished neural sensitivity to feedback, thereby influencing performance monitoring. In addition, several studies have reported an absence of the typical valence effect

(Ferdinand et al., 2012; Ferdinand, 2019; Fernandes et al., 2018; Hämmerer et al., 2011; Kardos et al., 2017; Mathewson et al., 2008; Pietschmann et al., 2011), which is commonly reflected in a larger FRN following negative compared to positive feedback and is considered an index of learning progress (Holroyd & Coles, 2002). In older adults, this pattern may be explained by a general slowing of learning, such that positive feedback remains relevant for a longer time. At the same time, age-related changes in dopaminergic transmission are thought to reduce sensitivity to feedback signals, particularly those related to reinforcement. This reduced dopaminergic sensitivity may impair efficient feedback processing, especially for negative feedback, and consequently limit rapid behavioral adjustment. However, another explanation, which will be elaborated in more detail in Chapter 1.3.2, could be that older adults focus more on positive feedback and thereby have an enlarged activity after positive feedback in their FRN.

With respect to the later processing stage, feedback-induced learning studies have shown inconsistent effects of age on working memory updating as indexed by the P3b. While some studies found no age-related reduced P3b amplitudes for older compared to younger adults in probabilistic selection, probabilistic learning, or time-estimation tasks (Ferdinand, 2019; Ferdinand & Kray, 2013; Schmitt et al., 2014a; West & Huet, 2020), others found smaller amplitudes for older adults in time production or gambling tasks (Kardos et al., 2017; Wild-Wall et al., 2009). These findings suggest that working memory updating is not reduced in older adults in general but more dependent on task or feedback characteristics and can influence behavioral performance (Lubitz et al., 2017). Furthermore, it has been shown that older adults, in contrast to their younger counterparts, show a less sensitive mechanism for task dependent information (Schmitt et al., 2014a) and again reduced differentiation between valence (Ferdinand, 2019; Kardos et al., 2017). Feedback-induced learning studies across aging, however, almost consistently reported topographical differences such as a

broader scalp distribution to frontal areas in older adults, possibly to compensate for age-related differences by recruiting additional resources (Cabeza et al., 2002; Davis et al., 2008; Eyler et al., 2011; Ferdinand, 2019; Kardos et al., 2017; Wild-Wall et al., 2009). This specific process will be introduced in Chapter 1.3.2.

Overall, age-related neurochemical and structural changes impact feedback-induced learning and alter processing stages associated with performance monitoring and working memory updating. At the same time, demographic shifts in society highlight the need to better understand how these age-related alterations in learning can be flexibly modulated or supported in older adults.

1.3 Possible compensatory mechanisms in aging

1.3.1 Theoretical account of compensatory scaffolding

Given these age-related differences, identifying ways to improve these has become a central objective in aging research. Accordingly, various approaches have been examined, among them potential compensatory mechanisms in cognitive aging. One theoretical model accounting for possible compensatory mechanisms is the revised Scaffolding Theory of Aging and Cognition (STAC-R) (Reuter-Lorenz & Park, 2014). It integrates biological aging, life experiences, brain structure and function, and compensatory mechanisms to explain both the level of cognitive performance and the rate of cognitive change in aging. The core idea is that aging leads to neural decline, but the brain actively compensates by recruiting additional neural resources ("Scaffolding") through different mechanisms. The effectiveness of this scaffolding depends on lifetime experiences and interventions. Life course experiences can either lead to neural resource enrichment, possibly through intellectual engagement and education, as well as physical exercise, and higher abilities, or to neural resource depletion, including genetic risk factors, stress, vascular

diseases, or low socioeconomic status. These two changes, as already mentioned in the previous chapter, are dependent on biological aging, which has been shown to be associated with reduced DA activity, neural network, cortical thickness and brain volume.

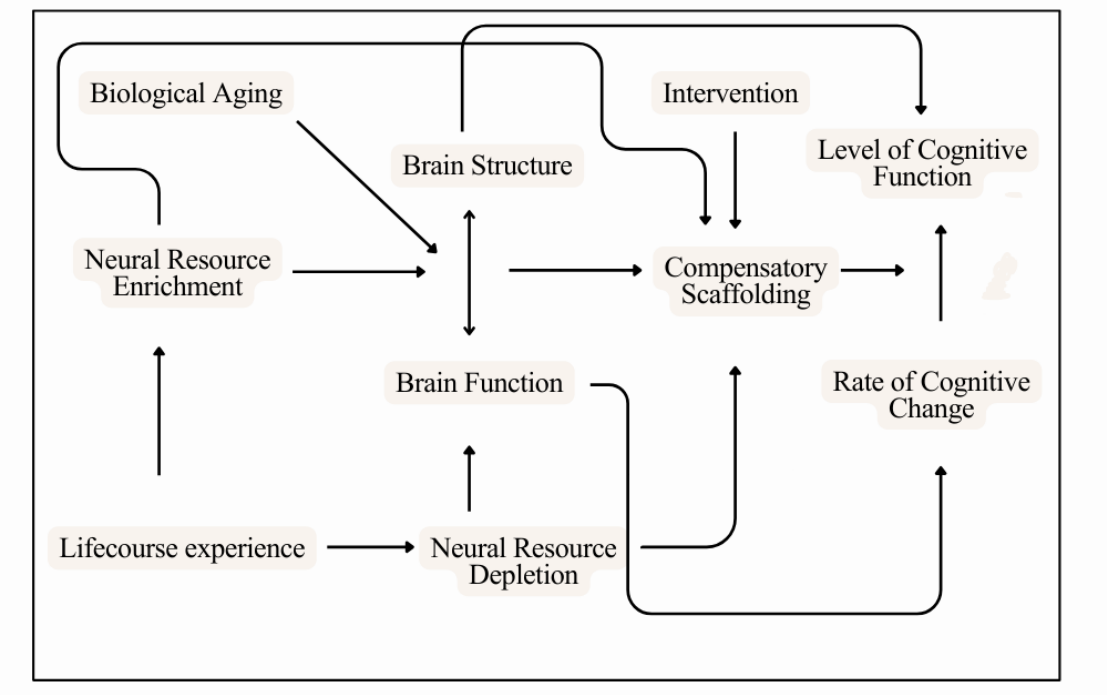
Scaffolding furthermore reflects positive brain plasticity in older age that counteracts age-related decline and becomes evident at both structural and functional levels. Compensatory scaffolding includes cognitive reserve as well as the recruitment and activation of additional or alternative brain regions to support cognitive performance. This compensation by an enhanced fronto-parietal recruitment has also been shown in two other prominent models postulating that older adults activate additional frontal resources, especially during higher effort task demands. The PASA (Posterior-Anterior Shift in Aging) Model (Davis et al., 2008; Kehoe et al., 2013) states that frontal activation goes along with posterior (parietal) underactivation to maintain performance and the CRUNCH-Model (Reuter-Lorenz & Cappell, 2008) extends these assumptions by stating that also younger adults show this effect when the task gets more difficult and needs more working memory capacity. However, these models also suggest that compensatory recruitment is not unlimited. In particular, the CRUNCH model proposes that older adults may reach a ceiling of available frontal resources at high task demands, beyond which compensatory activation can no longer be increased.

While brain structure and brain function directly lead to the level of cognitive function and rate of cognitive change, they can indirectly be influenced by compensatory scaffolding. Scaffolding can be directly supported by interventions, such as new learning, social/intellectual engagement, exercise, cognitive training, and meditation. Both the capacity for compensation and cognitive functioning itself depend on life-course experiences and current lifestyle factors. Older adults who, due to a healthy lifestyle and favorable genetic resources, are less affected by age-

related neural changes require less compensatory scaffolding than older adults, who experience more pronounced age-related decline. Overall, the STAC-R model highlights that cognitive aging reflects a dynamic balance between neural decline and adaptive compensation, showing that lifelong experiences and targeted interventions can substantially shape cognitive abilities and preserve mental functioning in older age. Figure 1.5 visualizes the simplified STAC-R model, which broadens the understanding of determinants of neural compensation.

Figure 1.5

Simplified illustration of the STAC-R Theory



Note. Adapted from Reuter-Lorenz and Park, 2014.

1.3.2 Preserved brain structures and functions in aging

As introduced in Chapter 1.2.1 and further elaborated at the level of biological aging within the STAC-R theory, aging is characterized by marked heterogeneity in brain trajectories, with some

neural systems showing relative preservation over time. For these brain systems, cognitive functioning mostly preserves in older age, as it is the case with crystallized intelligence (Salthouse, 2010). Beyond this, there is evidence that in contrast to pronounced age-related decline in prefrontal regions, limbic structures such as the amygdala appear comparatively stable in both structure and function. Functional neuroimaging studies have consistently demonstrated that the amygdala remains robustly responsive to emotional stimuli in aging and, in some cases, shows even heightened activation compared to younger adults, particularly in response to positive emotional material (Mather et al., 2004). This preserved or even enhanced amygdala responsivity suggests that bottom-up processing of emotionally salient information remains largely intact with increasing age, even though top-down cognitive control mechanisms supported by the prefrontal cortex become less efficient. Importantly, this preservation has direct consequences for the processing of emotional and social stimuli, as older adults typically show preserved or even superior performance in recognizing positive emotional facial expressions, while exhibiting selective decline in the recognition of negative emotions such as anger or fear (Ruffman et al., 2008). The superior processing of positive stimuli in aging has been intensively investigated in different cognitive functions, such as working memory, and has since been called “the positivity effect” or “positivity bias” (Carstensen et al., 2006; Mather & Carstensen, 2005; Reed et al., 2014; Reed & Carstensen, 2012). This preservation in structure and function across aging suggest that age-related differences in feedback-induced learning can be minimized by utilizing affective feedback.

1.3.3 Motivational aging theories

One family of approaches that try to explain the influences of the preserved brain structures in cognitive functioning across aging are motivational aging theories. These possibly could clarify

why stimuli containing social or emotional information could be particularly useful in learning from feedback during aging. First, the Socioemotional Selectivity Theory (SST), developed by Carstensen (1991), is a lifespan theory of motivation that explains how time perspective influences individuals' prioritization of social goals. The theory seeks to integrate motivational, developmental, and emotional processes across the lifespan. According to the SST, as people age and perceive their future time as increasingly limited, they shift their motivational focus from knowledge-related goals towards emotionally meaningful goals. The SST posits that this motivational reorientation is not only due to age, but to perceived time horizons. As such, similar patterns may evolve in younger individuals who experience time as constrained (e.g., in life-threatening situations or illness) (Carstensen et al., 1999; Carstensen, 1991, 2021). While age does not seem to be the leading factor, younger adults, however, tend to focus on preparatory goals, such as gaining knowledge or exploring new things. This shift, among other things, results in a greater emphasis on emotion regulation in older adults. Emotion regulation is the ability to control one's or other's emotions, a conscious and unconscious mechanism to shift the perceived emotion to a desired emotion (Braunstein et al., 2017; Thompson, 1994). The SST further assumes that during aging, more close social relationships to friends and family are sought. At the same time, the goal in aging is to pursue experiences that enhance well-being, conceptualized as the subjective experience of a high quality of life, including health, prosperity and life satisfaction (Diener et al., 1999; Ryff, 2013). Thus, although increased distress during aging might be assumed among older adults, the contrary has been demonstrated in empirical research, a phenomenon named the positivity paradox, reflecting better overall well-being (Carstensen et al., 2010; Stone et al., 2010), emotional experience (Carstensen et al., 2000; Gross et al., 1997), and greater emotional stability compared to younger adults (Brose et al., 2013; Carstensen et al., 2010).

The second theory, the Strength and Vulnerability Integration Theory (SAVI) uses a similar approach to describe a more positive well-being, associated with an increased emotion regulation strategy during aging, which may indirectly influence motivational processes (Charles, 2010; Charles & Luong, 2013; Charles & Piazza, 2024). This is grounded in the idea that older adults develop emotion regulation strategies, such as perspective taking, and show improved coping strategies, while tending to avoid negative emotions (Growney & English, 2023; Isaacowitz & Wolfe, 2024; Mather, 2012). At the same time, the model recognizes age-related vulnerabilities, including reduced physiological flexibility and a diminished capacity to adapt under high-arousal conditions. While emotion regulation may be generally more successful in older adults, situations that exceed a certain level of emotional intensity, particularly those involving negative affect, may undermine regulatory efficiency. In such circumstances, older adults may no longer benefit from their otherwise advantageous emotion regulation strategies and even be at a disadvantage compared to younger individuals, which can affect motivational processes. While SAVI predicts the positivity to be an emotion regulation strategy, the SST assumes it to be a motivational reorientation.

The phenomenon mentioned above may further account for the observed age differences in the processing of socio-emotional feedback. A meta-analysis conducted by Swirsky et al. (2023) examined the influence of motivational orientation on memory across age groups and showed that, overall, memory performance in older adults was enhanced following socio-emotional rewards, whereas younger adults benefited more from financial gains. Moreover, age-related shifts in motivational priorities have been shown to influence attentional and memory biases. A review by Mather and Carstensen (2005) revealed a robust positivity effect in older adults, demonstrating that older adults recalled more positively valenced stimuli than negative or neutral ones, although their overall recall remained lower than that of younger adults. In contrast, younger adults recalled a

comparable number of positive and negative stimuli, indicating no differentiation as a function of valence. These findings imply that memory processing in older adults is shaped by a preference for emotionally meaningful and positive information. In contrast, younger adults' memory strategies seem less influenced by socio-emotional relevance or valence and more by alternative factors.

Taken together, the STAC-R model provides a theoretical framework, which includes external and internal factors (such as less decline of limbic structures and frontal over engagement for performance), and eventually lead to compensatory mechanisms in older adults. SST and SAVI further provide complementary accounts of why older adults may benefit particularly from feedback containing social or emotional information. While SST emphasizes an age-related motivational shift toward emotionally meaningful goals, thereby increasing the subjective relevance and depth of processing of socio-emotional feedback, SAVI specifies the regulatory conditions under which such benefits are most likely to occur. Both theoretical approaches gather in suggesting that feedback aligned with older adults' emotional and motivational priorities is more likely to attract attention, promote engagement, and facilitate learning, as long as arousal does not exceed individuals' regulatory capacities.

1.4 Aging and learning from socio-emotional feedback

In the previous chapters, theoretical concepts of feedback-induced learning during aging were introduced. Motivational theories of aging furthermore posit a shift towards processing of positive and socio-emotional relevant information, pointing to a supportive role that adds to the biological changes during aging. These accounts suggest that compensatory mechanisms in older adults are present and that especially socio-emotional information may lead to learning benefits and be reflected in neural correlates during aging.

Across two studies, Gorlick et al.(2013, 2015) demonstrated that emotionally meaningful feedback can modulate age-related differences in learning under conditions of increased cognitive demand. In rule-based learning tasks, where rules have to be learned, maintained, and executed, age-related performance differences were minimized when older adults received socio-emotional feedback (in the form of faces), whereas point-based feedback showed no compensatory effects. Notably, the impact of socio-emotional feedback was dependent on valence and cognitive load, with negative emotional stimuli only supporting performance in older adults during high load conditions. This pattern suggests that socio-emotional feedback may alter the motivational relevance of task outcomes, thereby influencing engagement and performance when cognitive resources are taxed (Gorlick et al., 2013).

However, these behavioral effects did not generalize across learning domains. In procedural learning tasks, where no rule has to be explicitly learned, but rather automatic learning occurs through internal strategy development, socio-emotional feedback (in the form of faces) did not eliminate age-related deficits unless older adults adopted a rule-based strategy. Thus, the influence of socio-emotional feedback appears to depend on the learning strategy employed, with motivational effects emerging primarily when learning involves deliberate, goal-directed processes rather than automatic mechanisms (Gorlick & Maddox, 2015).

Findings from reversal learning paradigms underscore the positivity effect in older adults (Nashiro et al., 2011). They differ from rule-based tasks in a way that a rule switches unannounced, so there is a need for people to adapt cognitively flexible. Whereas younger adults' performance was largely unaffected by outcome valence, older adults showed reduced learning when correct responses were associated with negative outcomes, but relatively preserved performance when outcomes were positive. This asymmetry is consistent with age-related shifts in motivational

priorities and the positivity effect, whereby negative emotional outcomes may be less effectively utilized for updating stimulus–response associations in probabilistic learning tasks.

However, the studies discussed so far primarily examined learning from socio-emotional feedback at the behavioral level. By contrast, the extent to which these effects are reflected in more fundamental processes such as the detection of unexpected events and working memory updating has received comparatively little attention. Addressing this gap, Ferdinand and Hilz (2020) employed a probabilistic learning task using socio-emotional feedback (in the form of faces), contrasted with neutral faces presented on yellow and blue background to indicate positive or negative feedback. Replicating earlier findings, overall performance was higher in younger than in older adults. Importantly, however, age differences were observed at the level of feedback processing rather than behavioral performance alone.

While younger adults did not show a processing advantage for socio-emotional feedback, older adults exhibited enhanced early feedback processing, as reflected in the FRN. Unexpectedly, this effect was more pronounced in the neutral feedback condition, suggesting that neutral facial expressions may convey implicit valence-related information. At later stages of feedback processing, younger adults' working memory updating was primarily driven by valence and appeared largely independent of socio-emotional feedback. In addition, younger adults showed a clear parietal focus of working memory updating. Older adults showed enhanced working memory updating following socio-emotional feedback, indicating a stronger reliance on affective information during the integration of feedback. Furthermore, they updated their working memory more strongly after negative compared to positive feedback, which suggests that also for older adults, negative feedback was more relevant to perform the task successfully.

While the results of working memory updating matched the participants' learning performance with regards to accuracy measures, FRN results were rather unexpected. Several possible explanations could be responsible for these results. For older adults, as mentioned above, it was quite unexpected that they showed a larger detection of unexpected events after neutral in contrast to socio-emotional feedback, possibly because the neutral facial expressions were interpreted as rather negative. In light of this finding, an important question is whether seemingly neutral facial expressions are genuinely affectively neutral, or whether they inherently signal a particular emotional valence. It was further surprising that older adults showed enhanced FRN amplitudes as compared to younger adults. This could be due to the possibility that the probabilistic learning task was insufficiently demanding for younger adults, reducing their reliance on external feedback. While this study was amongst the first ones to investigate feedback-induced learning through socio-emotional feedback in older adults on an electrophysiological level, several open questions remained. The questions related to the nature of the socio-emotional feedback stimuli and to whether younger adults would likewise benefit from this type of feedback when task difficulty, which leads to increased working memory load, was used.

Numerous studies have demonstrated that increases in task difficulty are associated with slower learning progress and reduced performance in younger adults (Ferdinand, 2019; Luft, 2014). To this extent, the effects of task difficulty on younger adults are comparable to those commonly attributed to aging. These effects are commonly interpreted within the cognitive load theory and attributed to the limited capacity of working memory in younger adults (Kirschner, 2002; Sweller, 1994). While behavioral data largely converge in indicating detrimental effects of high working memory load (Arbel, 2020; Collins & Frank, 2012; Gorlick et al., 2013), the evidence at the neural level remains inconsistent. In particular, findings regarding the feedback-related negativity (FRN)

are mixed: some studies report reduced FRN amplitudes under high cognitive load, which has been interpreted as impaired processing of unexpected outcomes (Krigolson et al., 2012; Krigolson, 2018), whereas other studies find no modulation of the FRN by task difficulty or working memory load (Arbel, 2020; Ferdinand, 2019; Somon et al., 2019).

By contrast, working memory updating appears to be more sensitive to cognitive load. Several studies suggest reduced amplitudes or broader scalp distributions of the P3b under high load in younger adults, providing support for the CRUNCH-model (Arbel, 2020; Ferdinand, 2019; Polich, 2007; Reuter-Lorenz & Cappell, 2008; Tregellas et al., 2006). Differences in how the paradigms operationalize task difficulty and show the feedback can nevertheless hinder a clear interpretation of the available findings (Shiwei et al., 2022; Somon et al., 2019). While Ferdinand and Hilz (2020) did not report such effects in younger adults, it remains possible that under systematically increased working memory load, younger adults may exhibit processing and behavioral patterns comparable to those observed in older adults. This assumption is further supported by evidence from younger adults suggesting that social or socio-emotional feedback facilitates behavioral performance and modulates neural processing at both early and later stages of feedback evaluation (Hurlemann et al., 2010; Pfabigan et al., 2014, 2019; Pfabigan & Han, 2019; Schulreich et al., 2013).

Interestingly, as far as we know, there is sparse evidence for the impact of socio-emotional feedback characteristics in older adults, examining which specific characteristics of socio-emotional feedback can lead to a potential benefit in learning, thereby reducing age-related learning differences. While recent research primarily used socio-emotional feedback in the form of faces, which convey different characteristics, such as emotionality, but also sociality and communicative meaning, a break down into these facets could bring potential deeper insights.

Bellebaum et al. (2011) for example examined observational learning in older adults using a probabilistic selection task in two, active and observational learning, conditions and found that older adults learned comparably to younger adults, but benefited more from positive feedback. Feedback during observational learning could be interpreted as social as this involved a social situation. However, the presented study used only behavioral measures. Furthermore, observation based paradigms, in which participants learn from others' outcomes or evaluations (acceptance vs. rejection tasks) mainly focused on younger adults (Albrecht & Bellebaum, 2021; Dekkers et al., 2015; Koban et al., 2012; Kujawa et al., 2014; Molen et al., 2017; Rak et al., 2013; Voegler et al., 2019). In addition, social feedback has also been investigated using symbolic social stimuli such as thumbs-up versus thumbs-down gestures, which convey socially learned communicative meaning without requiring facial expressions (Pfabigan et al., 2019; Pfabigan & Han, 2019). Importantly, these studies found that such social signals can modulate feedback-related ERPs also in younger adults, underscoring their relevance for reinforcement learning mechanisms.

Nevertheless, in western cultures, these social symbols include a communicative meaning, which may have an influence on feedback-induced learning as well (Schmuecker & Pfabigan, 2025). Apart from this, breaking down socio-emotional feedback into its separate facets is, to date, difficult, as recent research primarily uses facial expressions for naming emotional feedback (Ferdinand & Hilz, 2020; Gorlick et al., 2013; Kamp et al., 2024; Weiß et al., 2020). Yet, emotional feedback can also be conveyed through emotionally charged words or emojis (Leue et al., 2020; Weiß et al., 2019) or the activation of internal emotional states (Olofsson et al., 2008).

To conclude, research on feedback processing in older adults has predominantly relied on facial expressions as feedback stimuli, which introduces a critical methodological confound. While such stimuli are valid, their multidimensional nature limits the identification of specific feedback

characteristics that drive age-related differences in feedback-induced learning. To isolate the cognitive and neural mechanisms underlying feedback processing across the lifespan, an experimental disentanglement of social, emotional and communicative feedback components is therefore required, even if this entails a more controlled, non-naturalistic paradigm. Building on lifespan theories of motivation, feedback-induced learning may be particularly enhanced in older adults when feedback aligns with age-related motivational orientations. However, establishing such effects necessitates a systematic and conceptually precise distinction between the above-mentioned feedback facets. Accordingly, the selection and design of feedback stimuli represent a central methodological challenge in feedback processing and aging.

2 Research questions

Discoveries from behavioral and EEG studies suggest that compared to younger adults, older adults may particularly benefit from feedback containing socio-emotional information in learning. However, it remains unclear whether this effect is primarily driven by age-related factors or by limitations in working memory capacity during learning. Moreover, there is a need to better understand which feedback characteristics are relevant to improve learning outcomes and whether age-related differences can be observed in the neural processing of feedback at early and later processing stages. The present doctoral thesis therefore seeks to address these issues by investigating the following research questions:

Study 1 (Chapter 3). Evidence that also younger adults can benefit from socio-emotional feedback during learning to date is inconsistent. One possible explanation is that younger adults may also benefit from such feedback under conditions of reduced cognitive resources. Accordingly, the first study examined whether increasing task difficulty, thereby imposing higher working memory load, would render socio-emotional feedback beneficial for younger adults during learning and influences neural feedback processing.

Study 2 (Chapter 4). The second study built on the assumption that facial expressions are inherently ambiguous rather than truly neutral and may be interpreted as more negative. Therefore, we refined the feedback stimuli by morphing emotional facial expressions into either strong or weak emotional expressions to achieve greater comparability between socio-emotional and neutral feedback in a probabilistic learning paradigm. This methodological improvement allowed us to test whether previously reported age-related differences in learning from feedback would still be observed under more carefully controlled stimulus conditions. In addition, we investigated whether

neural responses associated with feedback processing would exhibit increased specificity and reliability when stimulus confounds were minimized. The central research question of this study was whether older adults would continue to show superior learning following strong versus weak emotional feedback.

Study 3 (Chapter 5). Because the previous experiments did not allow for a clear differentiation between the social, emotional, and communicative components inherent in the facial stimuli, the third study was designed to isolate the basic social dimension of feedback. By systematically removing emotional and communicative components, this study aimed to determine whether basic social stimuli alone are sufficient to enhance learning, particularly in older adults. Furthermore, we examined how such effects are reflected in electrophysiological markers related to expectancy violation and working memory updating.

3 Study 1: The impact of emotional feedback in learning easy and difficult tasks - an ERP study

Authors: Braunwarth, Jana Isabelle[1]; Ferdinand, Nicola Kristina[1]

Affiliations: Department of Psychology, University of Wuppertal, Germany

Journal: This manuscript was published in *Cognitive, Affective and Behavioral Neuroscience* on 27th March 2025.

Status: Published

Funding: Open Access funding enabled and organized by Projekt DEAL. The present work was supported by the German Research Foundation (Grant FE 1247/2–2).

Acknowledgment: The authors thank Sari Pfotenhauer and Doménica Abendaño Burneo for helping with the data collection.

Conflict of Interest: The authors declare no conflict of interest.

Author´s contributions: **JI Braunwarth:** Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing: Original Draft Preparation, Writing: Review & Editing; **NK Ferdinand:** Conceptualization, Funding Acquisition, Methodology, Project Administration, Resources, Validation, Writing: Review & Editing, Supervision.

DOI: https://doi.org/10.3758/s13415-025-01284-2

Keywords: Feedback Processing, Feedback-Related Negativity (FRN), P3b, Emotionality, Working memory load

3.1 Abstract

Learning from the emotional reaction of others is crucial in our everyday lives. We assumed that additional emotional information could be especially beneficial, when a task is difficult and the limits of working memory capacity are reached. For this reason, we examined whether a potential benefit of emotional feedback during reinforcement learning is dependent on working memory load. In addition to learning performance, we analysed the neural mechanisms of reinforcement learning by examining two event-related potentials (ERPs), the Feedback-Related Negativity (FRN) and P3b. Participants were divided into two difficulty groups (with $n = 21$ in the difficult and $n = 22$ in the easy group), performing a learning task with emotional or non-emotional feedback. Task difficulty was manipulated by varying the number of the stimulus-response associations. Participants´ showed learning in all conditions. Emotional feedback led to increased accuracy and decreased reaction times in both groups. However, this benefit occurred earlier in the easy condition. The detection of unexpected events, as reflected in the peak-to-peak FRN, as well as working memory updating, as reflected in the P3b, were enhanced after emotional in contrast to non-emotional feedback for both groups. In contrast, task difficulty had no effect on the detection of unexpected events, but led to a P3b that was more evenly distributed over the scalp, which could indicate that additional frontal resources were recruited to perform the difficult task. Our results suggest that working memory load and emotional information independently influence feedback processing without interacting.

3.2 Introduction

Adjusting our behavior in response to feedback is a fundamental aspect of our daily interactions. Feedback not only informs us about the correctness of our decisions, but also serves as a source of learning, allowing us to modify future actions. In an earlier study, emotional feedback

led to better learning in older adults, whereas no benefit from emotional feedback was found in younger adults (Ferdinand & Hilz, 2020). This suggests that older adults were able to use the additional emotional information to compensate for age-related deficits, especially their decreased working memory capacity. This raises the question of whether younger adults' feedback processing is, in general, not susceptible for emotional information or whether younger adults would also be able to benefit from emotional information when their working memory capacity is pushed to its limits. This study therefore investigated feedback processing in a reinforcement learning paradigm under low and high working memory load in younger adults to get more insights on under which circumstances people benefit from emotional feedback and how this benefit is processed on a neural level by assessing two feedback-locked event-related potentials (ERPs): feedback-related negativity (FRN) and the P3b.

3.2.1 Learning from Feedback

During feedback-induced learning, distinct brain regions serve specific roles. The mediofrontal cortex, particularly the anterior cingulate cortex (ACC), and the mesencephalic dopamine system, are especially relevant for action monitoring (Cohen, 2008). Mesencephalic dopamine neurons show phasic increases for better-than-expected events and decreases for worse outcomes, serving as learning signals for the ACC (Alexander & Brown, 2011; Holroyd & Coles, 2002; Schultz, 2002). In the event-related potential, the Feedback-related Negativity (FRN), a negative deflection peaking at approximately 250 ms after feedback presentation and primarily generated in the dorsal ACC, is found and reflects the detection of unexpected (negative) events (Ferdinand & Opitz, 2014; Gehring & Willoughby, 2002; Miltner et al., 1997; Yeung et al., 2004). There are different approaches to measure early feedback processing. The mean amplitude FRN has been found to be affected by valence, feedback probabilities, and magnitude (for a review see

(Gheza et al., 2018; Martín, 2012), with an enhanced negativity after negative feedback or an enhanced positivity after rewarding feedback, thus indicating a signed prediction error. Therefore, over the past years, the term reward positivity (RewP) has also been coined (Holroyd et al., 2008b; Holroyd & Krigolson, 2007; Proudfit, 2015). In contrast, studies using a peak-to-peak measure of the FRN consistently found that it reflects the extent of the participant´s expectancy violation, i.e., the extent to which feedback is unpredicted by the participant. It has been demonstrated to be independent of the valence of the feedback and thereby may represent an unsigned prediction error (Ferdinand et al., 2012; Ferdinand & Kray, 2013; Oliveira et al., 2007; Pfabigan et al., 2011). This assumption is further strengthened by studies showing that the same expectancy manipulations that affect the peak-to-peak FRN also correlate with activation in the ACC (Ferdinand & Opitz, 2014). As we aim to examine the contribution of expectancy violations to learning from feedback in this study, we will focus on the peak-to-peak FRN in the following.

Following the detection of unexpected events, feedback undergoes further processing in order to lead to behavioral adaptation. According to the context updating theory, a P300 is elicited when an event is unexpected or novel, indicating the need for an update in the current cognitive context (Polich, 2007). The P300 is further subdivided into the P3a and P3b subcomponents, which differ in both function and topographical distribution. The P3a, which is typically observed over more frontal regions, is associated with the allocation of attentional resources to new stimuli. In contrast, the P3b, which displays a parieto-central topography, is linked to updating working memory with unexpected task-relevant information. The P3b is characterized by a positive deflection peaking between 300-500 ms post-feedback at parieto-central electrode sites, reflecting its role in integrating information into ongoing cognitive processing (Bellebaum & Daum, 2008;

Ferdinand et al., 2012; Martín, 2012; Mecklinger et al., 1994; Polich, 2007; Ullsperger et al., 2014; Walentowska et al., 2016).

3.2.2 Task Difficulty and Working Memory Load

Increasing task difficulty impacts learning, resulting in slower learning progress and diminished performance (Collins & Frank, 2012; Ferdinand, 2019; Gorlick et al., 2013; Luft, 2014). Consistent with the cognitive load theory, depending on the task, these are the results of a limited working memory capacity (Kirschner, 2002; Lin & Liang, 2021; Sweller, 1994). As a consequence, recent studies have explored how variations in task difficulty and their impact on working memory load influence feedback processing (Arbel, 2020; Ferdinand, 2019; Krigolson et al., 2015; Somon et al., 2019). For instance, Ferdinand (2019) investigated task difficulty in a probabilistic learning task with younger and older adults by manipulating the number of stimulus-response associations that had to be kept in working memory, and revealed slower learning in the more difficult condition. Similarly, Arbel (2020), explored task difficulty in a paired- association task with children, doubling the number of object-name pairs in the difficult condition and thereby increasing working memory load. They observed better performance in the easy as compared to the difficult task condition (for similar behavioral results, see Collins & Frank, 2012; Gorlick et al., 2013).

Results concerning the FRN are to date incongruent. For instance, Krigolson et al. (2015) investigated the neural mechanisms of reward processing by manipulating cognitive load in a time estimation task by adding a second task in the high cognitive load group. Despite similar behavioural task performance between groups, the high cognitive load group exhibited a less effective detection of unexpected events, reflected in a smaller peak FRN. The authors argued that

competing resources result in a less functional mediofrontal reward system. Similar results were also found by increasing the complexity of the feedback stimulus (Krigolson et al., 2012). In contrast, Ferdinand (2019) could not find an effect of task complexity on the peak-to-peak FRN in a probabilistic learning task, when the informational value of feedback stimuli was 100% valid. Also, Arbel (2020) and Somon et al. (2019) failed to find effects of working memory load on the FRN. Based on the latter studies, one would assume that even when working memory load is high, the early, automatic detection of prediction errors (reflected by the FRN) remains intact because this process relies on basic neural mechanisms that are not heavily influenced by the concurrent cognitive demands placed on working memory.

In contrast, ERP components like the P3b seem more strongly affected by working memory load, likely because they are involved in later stages of feedback processing, such as outcome evaluation and working memory updating, which are more reliant on attentional and working memory resources (Polich, 2007). Relatively few studies, however, investigated the influence of working memory load on the P3b during feedback-induced learning (Arbel, 2020; Ferdinand, 2019). Research examining the interaction between task complexity and feedback processing in reinforcement learning contexts has shown that under high working memory load, the ability to integrate feedback effectively can be impaired, leading to reduced P3b responses. For instance, Ferdinand (2019) found that the P3b after negative feedback was diminished in a task with a higher working memory load as compared to a task with a low load. Moreover, they found that the P3b was distributed more evenly over the scalp in the difficult task and concluded that additional frontal resources were recruited to perform the difficult task successfully (Cabeza et al., 2002; Ferdinand, 2019; Reuter-Lorenz et al., 2000; Tregellas et al., 2006). Arbel (2020) found that the P3b was less activated in children in the difficult task as well. Conversely, in an N-back task, working memory

updating as indicated by the P3b was not sensitive to a higher cognitive load at all (Shiwei et al., 2022). Additionally, in a modified Flanker task, conducted by Somon et al. (2019), an increase in task difficulty by increasing the flanker´s task difficulty (with congruent and incongruent arrowheads) led to an enhanced P3b. The authors suggested that an enhanced insecurity led to a larger activation (i.e., needs more working memory updating). It should be noticed, however, that this task is no genuine learning paradigm and additionally puts participants under time pressure to provoke errors, both of which can fundamentally influence the cognitive processes involved.

In addition to reconciling inconsistent findings on the detrimental effects of increased working memory load — induced by an increased number of stimulus-response associations — on learning and feedback processing, the present study also aims at examining whether these detrimental effects can be mitigated by other relevant factors like socioemotional feedback.

3.2.3 Socio-emotional Feedback

Feedback with socioemotional information is pervasive in daily life and considered particularly relevant and motivating (Adolphs, 2009; Rolls, 2000; Ruff & Fehr, 2014). Thus, numerous studies have explored social dynamics and their impact on performance (Boksem et al., 2011a, 2011b; Koban & Pourtois, 2014; Meel & Heijningen, 2010; Rak et al., 2013; Thoma & Bellebaum, 2012), while others investigated how facial stimuli influence feedback processing (Dekkers et al., 2015; Ferdinand & Hilz, 2020; Hurlemann et al., 2010; Pfabigan et al., 2014; Schulreich et al., 2013; Stavropoulos & Carver, 2014). Hurlemann et al. (2010), for instance, used social (happy vs. angry faces) and non-social (red vs. green light) feedback in a paired-association task, and found better performance after social feedback. Pfabigan et al. (2014) used a time estimation task to investigate whether social (happy vs. angry faces) as compared to non-social (+

vs. -) feedback would strengthen feedback processing. However, they found no influence of feedback type on the peak-to-peak FRN, possibly due to perceptual differences in stimulus complexity (Liu & Gehring, 2009; Matyjek et al., 2020; Pfabigan et al., 2015). To address this, Pfabigan et al. (2019) developed similar social (thumps up vs. thumps down) and non-social (+ vs. -), complex and non-complex stimuli and found an enlarged peak-to-peak FRN for social stimuli in a similar task. Nevertheless, time estimation tasks are not designed to show learning over time, thus conclusions concerning a possible learning benefit for social feedback are rather limited.

Therefore, Sailer et al. (2024) used a probabilistic reward learning task, but did not find an advantage of social over non-social feedback. In contrast, Ferdinand and Hilz (2020) used a probabilistic learning task with emotional (happy vs. disgusted) or non-emotional (neutral) face feedback to investigate learning across age groups and found enhanced learning from emotional feedback in older adults. Neutral faces, however, elicited larger peak-to-peak FRNs than emotional faces, most probably due to their unexpectedness and maybe even negative connotation in everyday communication. As for working memory updating, some studies have found that participants exhibited larger P3b amplitudes after emotional stimuli, indicating stronger updating processes due to heightened feedback relevance (Pfabigan et al., 2014, 2019; Schulreich et al., 2013).

However, Ferdinand and Hilz (2020) found that older adults benefited from emotional feedback during learning, while younger adults showed no such effect. This suggests that older adults were able to use the additional emotional information to compensate for age-related deficits during learning from feedback, which could be mainly due their decreased working memory capacity.

This raises the question of whether younger adults' feedback processing is, in general, not susceptible for emotional information or whether younger adults would also be able to benefit from emotional information when their working memory capacity is pushed to its limits. Taken together, the results of studies on feedback processing with socioemotional information are inconsistent. This is partly due to methodological challenges in creating perceptually comparable conditions. Also, working memory load has not explicitly been investigated in this context, so differences due to different working memory load of the tasks or between participants cannot be excluded.

3.2.4 The Present Study

This study therefore aimed to explore whether a potential benefit of emotional feedback during learning and feedback processing is dependent on working memory load in younger adults. To this end, we conducted a probabilistic learning task including emotional and non-emotional feedback and manipulating working memory load by varying the amount of to-be-learned stimulus-response associations. Additionally, we aimed at carefully controlling the feedback stimuli for visual complexity and thus used similarly complex emotional and non-emotional feedback stimuli by scrambling faces for the non-emotional condition. With this approach, we aimed to ensure that only one condition contained emotional information. We assumed that young participants would benefit from emotional feedback in more difficult tasks when reaching their processing limit, i.e., when working memory load is high. This should be visible in learning performance, i.e., reduced reaction times and increased accuracy. Emotional feedback should also lead to strengthened feedback processing. Specifically, emotional feedback should be followed by an enhanced detection of unexpected events in the difficult task as reflected by a larger peak-to-peak FRN as well as enhanced working memory updating as indicated by an enlarged P3b. Lastly, we expected

a frontal shift of the P3b in the difficult group, indexing the recruitment of additional frontal resources to successfully perform the more difficult task.

3.3 Methods

3.3.1 Participants

An a-priori conducted power analysis with a power of .8, effect size of .15 and α= .05 revealed the need for 18 participants for each group. To account for possible drop-outs, we recruited 25 younger adults between 19 and 29 years for each group. Inclusion criteria were right handedness, no psychiatric or neurological diseases, and normal or corrected-to-normal vision. Three participants were excluded due to excessive EEG artifacts, one for left-handedness, another for insufficient learning performance (in no learning quarter and feedback condition accuracy above chance level), and two for insufficient number of negative trials (< 20). The final sample consisted of *n*=22 participants in the easy group (mean age = 22.5 years, *SD*=3.05; 12 women) and of *n*=21 participants in the difficult group (mean age = 22.9 years, *SD*=2.46; 10 women).

Participants were recruited through social media and university specific websites and either received course credit or 25€ expense allowance. We followed the Declaration of Helsinki. The study was approved by the ethics committee of the University of Saarland and this positive vote was acknowledged by the ethics board of the University of Wuppertal after transferring the project. All participants signed informed consent before participation.

3.3.2 Stimuli

In the present study, participants completed a probabilistic learning task in four learning blocks (adapted from Ferdinand & Hilz, 2020), in which they learned a stimulus-response

association by pressing a button followed by feedback. The stimuli consisted of different object groups such as furniture and were taken from a standardized object database (Snodgrass & Vanderwart, 1980). Each object had a size of 281x197 or 197x281 pixel. Every learning block comprised six objects, with three objects connected to emotional and three objects connected to non-emotional feedback, counterbalanced across participants. The feedback stimuli were taken from the FACES database (Ebner et al., 2010) and had a pixel size of 161x201.

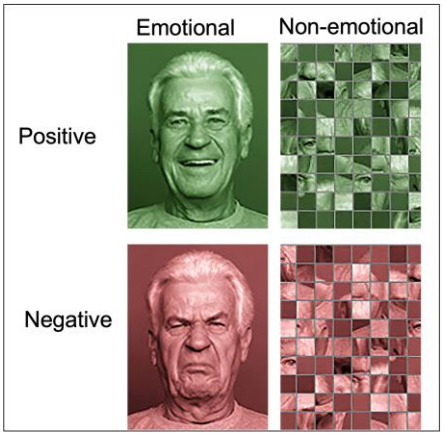
Analogous to the study by Ferdinand and Hilz (2020), the emotional feedback condition consisted of happy faces for positive and disgusted faces for negative feedback. The non-emotional feedback condition consisted of neutral faces of the same database. However, neutral faces might still provoke negative emotional reactions (Ferdinand & Hilz, 2020). Therefore, because equally complex feedback stimuli were needed for the emotional and non-emotional condition, the neutral faces were scrambled to create non-emotional stimuli that were similarly complex to emotional faces without emotionality (Liu et al., 2014; Pfabigan et al., 2015; Shigeto et al., 2011) but still contain parts of a face as research has shown that different brain areas are activated during face vs. object processing (Itier & Taylor, 2004; McCarthy et al., 1997; Sergent et al., 1992). The stimuli were scrambled using the scramble function of webmorph.org (DeBruine, 2018) with a size of 14x14mm for each scramble.

To address age and gender biases, four faces (young woman, old woman, young man, old man) were counterbalanced across participants leading to participants seeing only one of the four faces as feedback stimulus, but all four faces being used equally often in the experiment. To mark correct vs. incorrect response feedback, emotional and non-emotional feedback stimuli were coloured in green for positive and red for negative feedback. These colours intuitively indicate right or wrong as do the emotions in the emotional condition and should be helpful for

discriminating between positive and negative feedback (Figure 3.1). All images appeared on a grayscale background.

Figure 3.1

Emotional and non-emotional positive and negative feedback stimuli



3.3.3 Task

Participants in the easy group were instructed to act as moving helpers, deciding whether objects belonged in the black or white truck. They used coloured response keys ("c" for black, "m" for white) for item allocation and received feedback from their boss on their choices (Figure 3.2). Participants in the difficult group performed a similar task but had to allocate objects into two out of four trucks using different coloured keys ("c" for black, "v" for orange, "n" for blue, "m" for white).

With this approach, we aimed at increasing the load on working memory by doubling the number of associations to learn. Specifically, participants first had to find the one correct key, memorize it and additionally find the second correct key out of the above-mentioned four keys. For instance, in one of the learning blocks, participants were tasked with allocating items from the category "fruits". They had to determine that the black and white trucks were the correct choices

for the trials in which the apple appeared, while the blue and orange trucks were the appropriate selections in the trials, showing the banana. In every trial, only one response could be given.

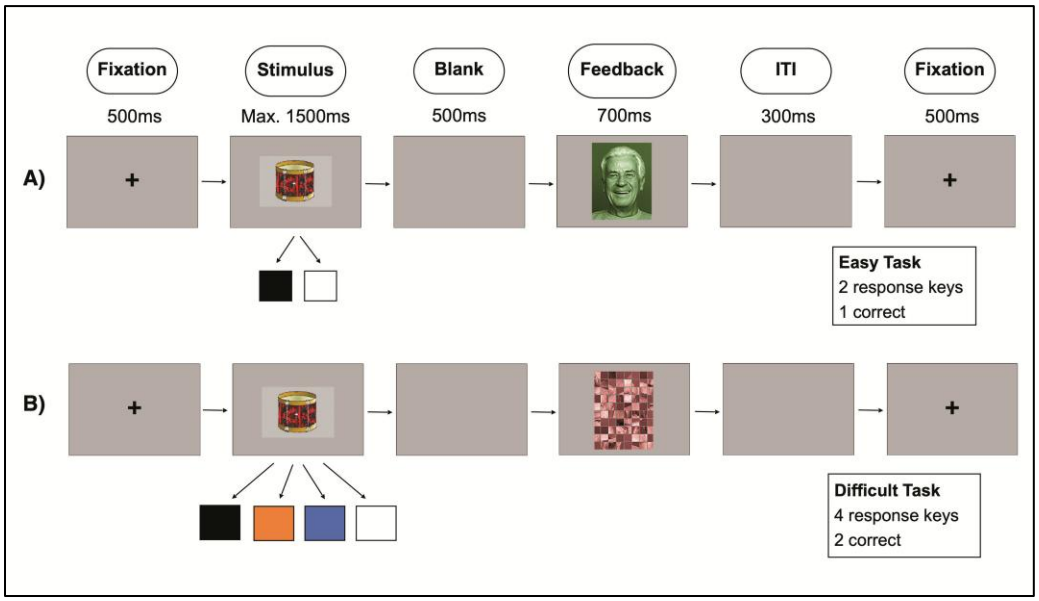
In the difficult condition, this meant that across multiple trials with the same object—mostly with other trials in between—participants needed to learn both correct responses. After each block, participants in both groups completed a brief retrieval task on object assignments, receiving feedback on their accuracy at the end. For this, every object was shown once and participants had to press the correct association button. In the difficult group, it was emphasized that pressing the same button twice for an object was not allowed. This was done to ensure that participants in the difficult condition actually tried to learn two out of four correct responses for each object.

The probability of receiving valid feedback was 90%. 10% of the presented feedback was invalid, so one-trial learning could be prevented (Eppinger et al., 2008; Ferdinand & Hilz, 2020; Holroyd & Coles, 2002). Participants were informed about the possibility of receiving invalid feedback. It was explained that, due to the supervisor's high workload, not all allocations were reviewed accurately, which in rare cases could lead to negative feedback even though the participants' allocations had been correct, and vice versa. However, it was emphasized that such instances of invalid feedback would occur only rarely. Response time was individually adapted (600-1500ms) based on participants´ performance. With this approach, we aimed at minimizing individual differences within a group mainly concerning the timeouts. The experiment started with 1000ms in the first trial. In case of exceeding this time, participants received a message on the screen stating "zu langsam" (German for "too slow"). Participants within the specified time range for 20 trials received a 100ms reduction for the subsequent 20 trials. If they exceeded the limit once, the time range remained unchanged for the next 20 trials. Exceeding the time window more than once resulted in a 100ms increase for the next 20 trials. The experiment consisted of 720 trials

divided into four learning blocks, each containing 180 trials. Each block was divided into four learning quarters for analyses. All Participants practiced eight trials of the easy condition with the option to repeat if desired. The difficult group performed 90 trials of the easy condition to assess whether there were pre-existing differences between the groups and to ensure a more comparable analysis across conditions. Short breaks with flexible duration were allowed every 60 trials.

Figure 3.2

Exemplary trial procedure and timing for A) easy and B) difficult task



3.3.4 Procedure

After the participant arrived, the consent form was signed. To assess handedness, participants were asked to fill out the Edinburgh Handedness Questionnaire (Oldfield, 1971), followed by a paper-pencil version of the digit symbol substitution test (DSST) (Jaeger, 2018). Moreover, they completed a demographic survey, addressing aspects such as exercise, nutrition, and social participation. Further questionnaires included the Emotion Regulation Questionnaire

(Abler & Kessler, 2011) and the German version of the Interpersonal Reactivity Index (IRI) (Paulus, 2009). We used the IRI as empathy has been shown to affect social feedback processing (Albrecht & Bellebaum, 2021; Meel & Heijningen, 2010).

Additionally, participants performed a digital version of the Mehrfachwahl-Wortschatz-Intelligenztest (MWT-B; Lehrl, 2005). Participants then were prepared for EEG recording and started the probabilistic learning task. They were seated in an electrically shielded and sound-proof EEG cabin in front of a 27-inch screen within a distance of 60cm. After the experiment, participants were asked to fill out follow up questions regarding their last night´s sleep, concentration and strategies used during learning. They then received expense allowance and left.

3.3.5 EEG Recording and Analysis

EEG was recorded using BrainVision Recorder (Version 1.23.0001, Brain Products GmbH, Gilching, Germany) and the paradigm was presented by E-Prime 3.0 (Psychology Software Tools, Pittsburgh, PA). 58 active silver/silver chloride electrodes were attached according to the international 10-20 system (Jasper, 1958) to an elastic electrode cap. The ground electrode was placed at position AFz and the left mastoid served as online reference. An electrooculogram (EOG) was recorded for offline eye movement correction. Therefore, electrodes were placed supra- and infraorbitally to the right eye and near the outer canthi of both eyes. All impedances were kept below kΩ 20. EEG and EOG were filtered online using a low pass filter (250Hz) and digitized with a sampling rate of 500Hz. Data were preprocessed using Matlab R2017b (The Mathworks Inc., Natick, Massachusetts, USA) and the eeglab toolbox v.2021.1 (Delorme & Makeig, 2004). The EEG data were downsampled to 250Hz, and filtered offline with a high pass filter of 0.01Hz and a

low pass filter of 30Hz. To balance the signal across hemispheres, data were re-referenced offline to the average of the two mastoids.

An independent component analysis was performed to extract eye movement related components from the data. We then used IClabel to flag those artifacts, additionally checked those manually, and discarded eye movement related components from the data (Pion-Tonachini et al., 2019). Afterwards, epochs were averaged for each subject and condition for the relevant segments (emotional positive, emotional negative, non-emotional positive, non-emotional negative feedback) and were cut using a time window of 900ms including a pre-stimulus baseline of -100ms using ERPlab v8.30 (Lopez-Calderon & Luck, 2014). Lastly, epochs exceeding 75μV were removed in an additional artefact rejection step. Based on previous literature, we decided to calculate the peak-to-peak FRN by subtracting the negativity of a time window of 240ms to 340ms from the preceding positivity in a time window of 180ms to 240ms post emotional feedback presentation at channel FCz (Ferdinand et al., 2012; Ferdinand & Hilz, 2020; Holroyd et al., 2006). After visual inspection however, we found this time window was not suitable for the non-emotional condition, because too many peaks were not adequately captured. A possible reason for this could be that the scrambled stimuli led to a prolonged FRN because of a higher complexity (Pfabigan et al., 2019). We then decided to use a collapsed localizer approach (Luck & Gaspelin, 2017) and used a time window of 180-300ms to determine the P2 peak and of 240-370ms to determine the N2 peak for both groups and all conditions at channel FCz. The P3b was measured from the mean value between 350ms and 550ms. This time window was taken based on previous studies (see Martín, 2012) and after visual inspection. To be able to examine difficulty related frontal shifts, the P3b was analysed at three midline electrodes: Fz, Cz and Pz.

3.3.6 Data Analysis

In the present study, we employed a between-subjects design to minimize potential exhaustion effects among participants, which could arise from the substantial number of trials required for robust ERP analyses (Boudewyn et al., 2018). Additionally, we controlled for fluid and crystallized intelligence between groups and conducted a baseline analysis to assess any differences between the groups to make a comparison more feasible. Thus, we conducted mixed repeated measures ANOVAs for accuracy and reaction times, with Task Difficulty (easy, difficult) as a between-subject factor and Feedback Condition (emotional, non-emotional) and Learning Quarter (1,2,3,4) as within-subject factors. Trials with reaction times <100ms were excluded from behavioral analyses.

Additionally, incorrect trials were excluded from the reaction time analyses. In case of significant main effects and interactions including the factor Learning Quarter, only pairwise comparisons for Learning Quarter 1 vs. Learning Quarter 2, Learning Quarter 2 vs. Learning Quarter 3 and Learning Quarter 3 vs. Learning Quarter 4 will be reported to reduce the number of comparisons. The Peak-to-peak FRN was analysed using a mixed-repeated measures ANOVA with Task Difficulty as a between-subject factor and Feedback Condition (emotional, non-emotional) and Valence (positive, negative) as within-subject factors at channel FCz. Mean P3b analysis employed a mixed-repeated measures ANOVA with Task Difficulty as a between-subject factor, and Feedback Condition (emotional, non-emotional), Valence (positive, negative), and Channel (Fz,Cz,Pz) as within-subject factors.

Since we assume topography differences, planned contrasts comparing Fz vs. Cz and Cz vs. Pz were included. As there is evidence that ERPs change over time and during learning, we

included an additional control factor Learning Half (first, second) in a further ANOVA (Eppinger et al., 2008; Holroyd & Coles, 2002; Wurm et al., 2020). However, since a change in ERPs over time was not part of our hypotheses, we report those effects in the supplementary material. Greenhouse-Geisser correction was applied for sphericity violations, and Bonferroni correction was used for post-hoc testing. If the assumption of sphericity was violated, the Greenhouse-Geisser correction was applied to both behavioral and ERP data. The adjusted p-values, and uncorrected degrees of freedom, are reported. Significance level was set to $\alpha = .05$. All analyses were performed in R Studio Version 3.6.3 (R Core Team, 2020).

3.4 Results

3.4.1 General Group Differences

To control for baseline group differences and differences in confounding variables, performance in the easy baseline trials as well as in the measures for fluid and crystallized intelligence were compared. The ANOVA with the between-subject factor Task Difficulty (easy, difficult) and the within-subject factor Feedback Condition (emotional, non-emotional) did not reveal any differences in reaction times or accuracy and no interactions with Feedback Condition (all *p*-values >.29). Possible group differences for fluid and crystallized intelligence were analysed using t-tests and revealed no effects in the MWT-B or DSST (all *p*-values>.47). Lastly, we analysed empathy scores between groups using t-tests, resulting in no significant differences (all *p*-values >.32).

3.4.2 Accuracy

The mixed repeated measures ANOVA with the between-participants' factor Task Difficulty (easy, difficult) and the within-participants' factors Feedback Condition (emotional,

non-emotional) and Learning Quarter (Q1, Q2, Q3, Q4) resulted in a main effect for Feedback Condition ($F(1,41)=5.09$, $p=.029$, $\eta_p^2=.11$), revealing that emotional feedback led to higher accuracies than non-emotional feedback. Further, significant main effects were found for Task Difficulty ($F(1,41)=29.09$, $p<.001$, $\eta_p^2= .42$) and Learning Quarter ($F(1,41)=135.04$, $p< .001$, $\eta_p^2=.77$) as well as an interaction between Task Difficulty and Learning Quarter ($F(3,123)=3.42$, $p=.029$, $\eta_p^2=.08$). Post-hoc tests showed that accuracy was worse in the difficult than the easy group in all four learning quarters (Q1: $t(75.9)=-5.81$, $p<.001$); Q2: $t(69.7)=-6.51$, $p<.001$); Q3: $t(57.3)=-5.69$, $p<.001$, Q4: $t(57.7)=-5.01$, $p<.001$). In the difficult group, accuracies increased from Learning Quarter 1 to 2 ($t(41)=-5.38$, $p<.001$), Learning Quarter 2 to 3 ($t(41)=-5.74$, $p<.001$), and Learning Quarter 3 to 4 ($t(41)=-3.66$, $p=.004$). For the easy group, accuracies also increased from Learning Quarter 1 to 2 ($t(43)=-13.89$, $p<.001$) and Learning Quarter 2 to 3 ($t(43)=-4.53$, $p<.001$), whereas no significant change in accuracy was found from Learning Quarter 3 to 4 ($p=.371$). No significant interactions including the factors Feedback Condition and Task Difficulty were found (all p-values $>.080$).

3.4.3 Reaction Times

To analyse reaction times, we conducted a mixed repeated measures ANOVA, analogous to the one for assessing accuracy. A main effect for Task Difficulty ($F(1,41)=6.08$, $p=.018$, $\eta_p^2=.13$), indicating faster reaction times in the easy than the difficult condition, and a main effect of Learning Quarter ($F(3,123)=24.71$, $p<.001$, $\eta_p^2=.37$), showing decreasing reaction times, were found. In addition, a main effect for Feedback Condition ($F(1,41)=7.78$, $p=.008$, $\eta_p^2=.16$) and interactions between Learning Quarter and Feedback Condition ($F(3,123)=3.26$, $p=.024$, $\eta_p^2=.07$)

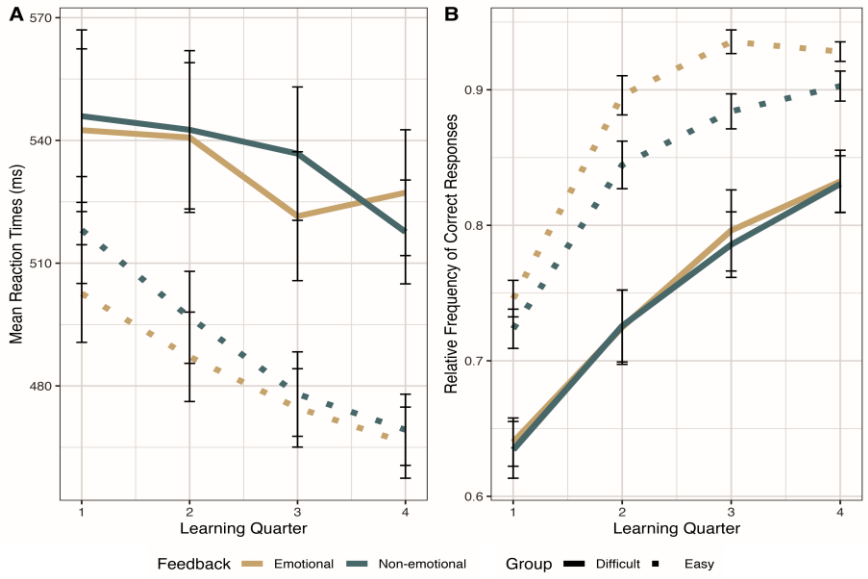
and between Task Difficulty, Learning Quarter and Feedback Condition were revealed ($F(3,123)=3.08$, $p=.030$, $\eta_p^2=.07$).

To resolve these interactions, we conducted ANOVAs separately for each group (Figure 3.3). The analysis for the easy group resulted in main effects for Feedback Condition ($F(1,21)=8.70$, $p=.008$, $\eta_p^2=.29$), Learning Quarter ($F(3,63)=30.2$, $p<.001$, $\eta_p^2=.59$) and their interaction ($F(3,63)= 2.83$, $p=.046$, $\eta_p^2=.12$). Post-hoc t-tests showed decreasing reaction times over learning quarters after emotional (Q1 vs. Q2 ($t(21)=3.42$, $p=.015$) , Q2 vs. Q3 ($t(21)=3.15$, $p=.029$), Q3 vs. Q4 ($t(21)=3.14$, $p=.03$) as well as after non-emotional feedback (Q1 vs. Q2 ($t(21)=3.27$, $p=.022$), Q2 vs. Q3 ($t(21)=4.84$, $p<.001$), Q3 vs. Q4 ($t(21)=3.16$, $p=.029$). Additionally, participants in the easy group had faster reaction times after emotional than non-emotional feedback in Learning Quarter 1 ($t(21)=-2.76$, $p=.012$) and 2 ($t(21)=-2.39$, $p=.026$), whereas no such effect was found for Learning Quarter 3 and 4 (all p-values >.26). The analysis for the difficult group revealed a main effect for Learning Quarter ($F(3,60)=4.79$, $p=.025$, $\eta_p^2=.02$) and an interaction between Feedback Condition and Learning Quarter ($F(3,60)=3.22$, $p=.029$, $\eta_p^2=.14$).

Post-hoc t-tests revealed shorter reaction times after emotional than non-emotional feedback in Learning Quarter 3 only ($t(20)=-2.85$, $p=.01$). After emotional feedback, reaction times significantly decreased from Learning Quarter 2 to 3 only ($t(20)=3.33$, $p=.02$), whereas no significant differences were found between Learning Quarter 1 vs.2 ($p=1$) and Learning Quarter 3 vs. 4 ($p=1$). After non-emotional feedback, reaction times significantly decreased between Learning Quarter 3 vs.4 ($t(20)=3.66$, $p=.009$), whereas no such effects were found between Learning Quarter 1 vs. 2 ($p=1$) and Learning Quarter 2 vs.3 ($p=1$).

Figure 3.3

Mean reaction times and accuracy



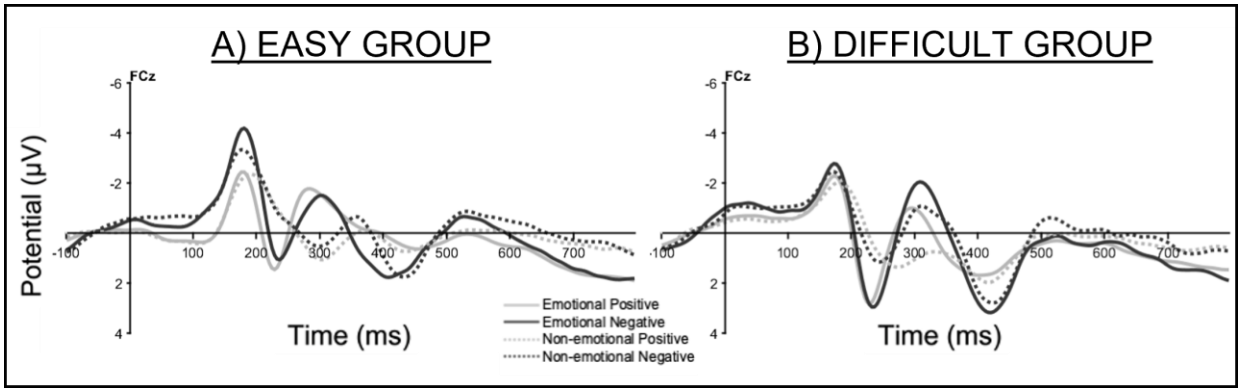
Note. A) Mean reaction times and B) accuracy across learning quarters for both difficulty groups and feedback conditions (whiskers denote standard error of the mean).

3.4.4 Peak-to-Peak FRN

The ANOVA with the factors Task Difficulty (easy, difficult), Feedback Condition (emotional, non-emotional), and Valence (positive, negative) on the peak-to-peak FRN at electrode FCz (Figure 3.4) revealed a main effect for Feedback Condition ($F(1,41)= 57.56$, $p<.001$, $\eta_p^2 =.58$), showing a larger peak-to-peak FRN after emotional than non-emotional feedback. Additionally, a main effect for Valence ($F(1,41)= 11.47$, $p= .002$, $\eta_p^2 = .22$) was found, reflecting a larger peak-to-peak FRN after negative than positive feedback. No main effect of Task Difficulty ($p=.054$) nor a significant interaction with Task Difficulty was revealed (all p-values >=.13).

Figure 3.4

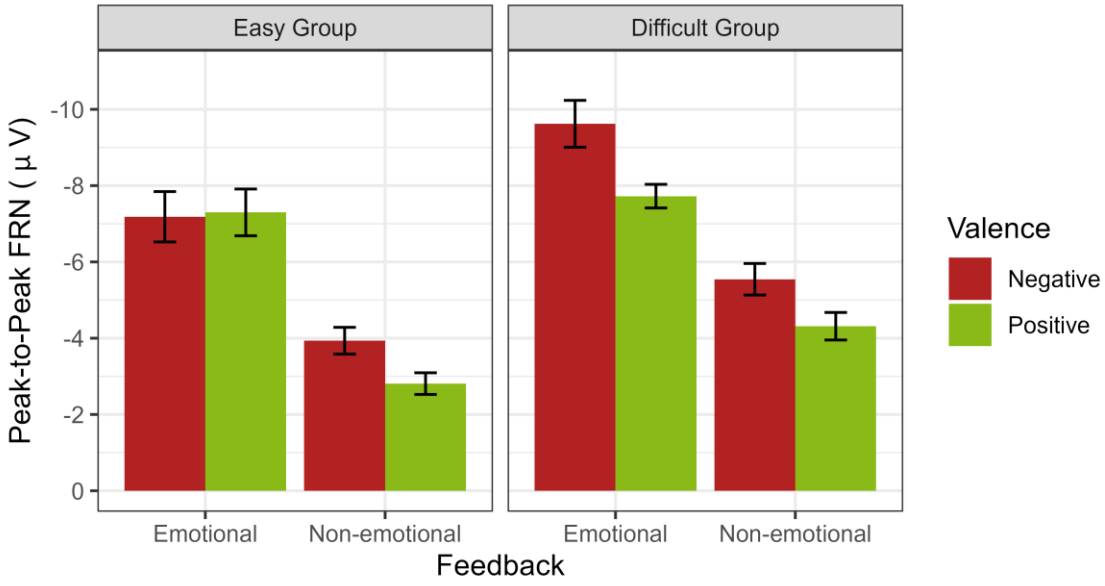
FRN waveform



Note. Feedback-locked ERP waveforms at Channel FCz for A) easy and B) difficult group. The time range of the peak-to-peak FRN is marked.

Figure 3.5

Peak-to-peak FRN bar graph



Note. Peak-to-peak FRN at channel FCz for both groups and emotional and non-emotional feedback.

3.4.5 P3b

The ANOVA with the factors Task Difficulty (easy, difficult), Feedback Condition (emotional, non-emotional), Valence (positive, negative), and Channel (Fz, Cz, Pz) on mean amplitude P3b identified significant main effects for Feedback Condition ($F(1,41)=5.39$, $p=.025$, $\eta_p^2=.12$) and Channel ($F(2,82)=22.19$, $p<.001$, $\eta_p^2=.35$. In addition, two-way interactions between Task Difficulty and Channel ($F(2,82)=7.39$, $p=.003$, $\eta_p^2=.15$), Valence and Channel ($F(2,82)=5.58$, $p=.005$, $\eta_p^2=.12$), and Feedback Condition and Channel ($F(2,82)=11.45$, $p<.001$, $\eta_p^2=.22$) emerged (Figure 3.7).

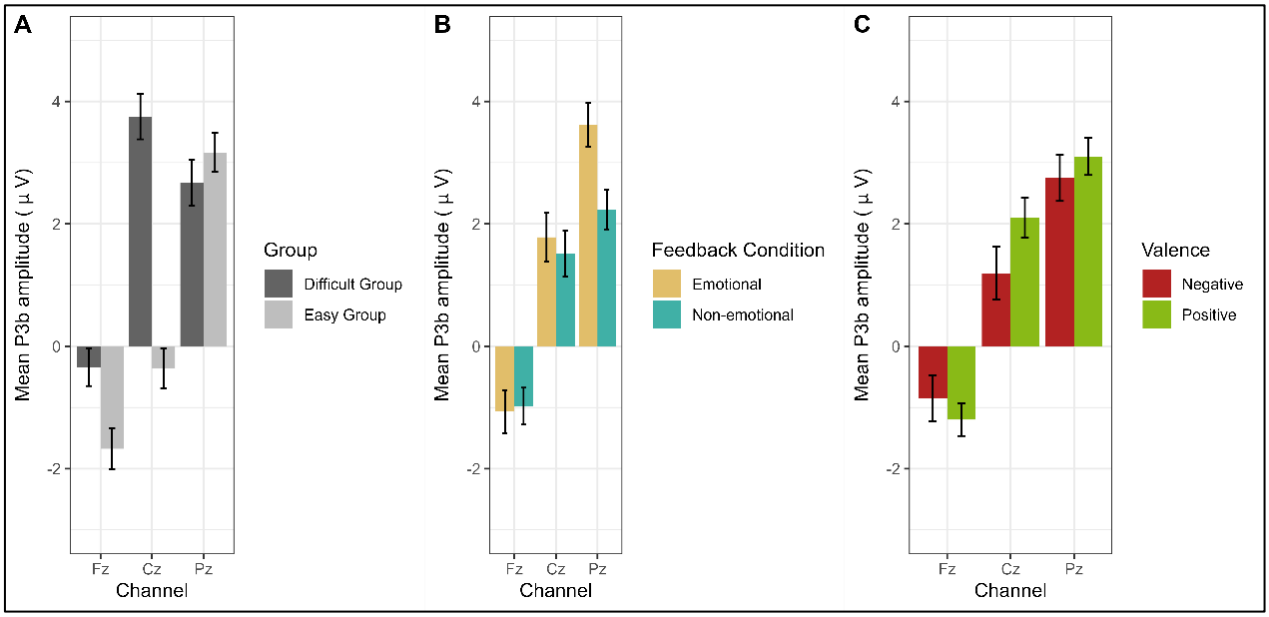
The analysis of the interaction between Task Difficulty and Channel (see Figure 3.6A) revealed significant amplitude differences across electrode sites. In the easy condition, the P3b had a clearly parietal topography as its amplitude was larger at Pz vs. Cz ($t(175)=-10.2$, $p<.001$) and larger at Cz vs. Fz ($t(175)=-5.00$, $p<.001$). In the difficult condition, P3b amplitudes were larger at Cz vs. Fz ($t(167)=-12.7$, $p<.001$) and larger at Cz vs. Pz ($t(167)=2.4$, $p=.045$), revealing a central P3b maximum. Also, the P3b was larger in the difficult than the easy group at electrode Fz ($t(340.94)=2.93$, $p=.003$) and Cz ($t(335.55)=8.28$, $p<.001$), whereas no difference was found at Pz ($p=.31$).

The interaction between Feedback Condition and Channel (see Figure 3.6B) revealed that only at the parietal electrode Pz, emotional feedback led to a significant larger amplitude than non-emotional feedback ($t(171)=6.35$, $p<.001$), whereas this was not the case for Cz ($p=.18$) and Fz ($p=.68$). Also, P3b amplitude after emotional feedback was larger at Pz vs. Cz ($t(171)=-4.05$, $p<.001$) and Cz vs. Fz ($t(171)=9.23$, $p<.001$). After non-emotional feedback, the mean P3b

amplitude was larger at Cz vs. Fz ($t(171) = 7.98$, $p < .001$), whereas no difference was found for Cz vs. Pz ($p = .229$).

Figure 3.6

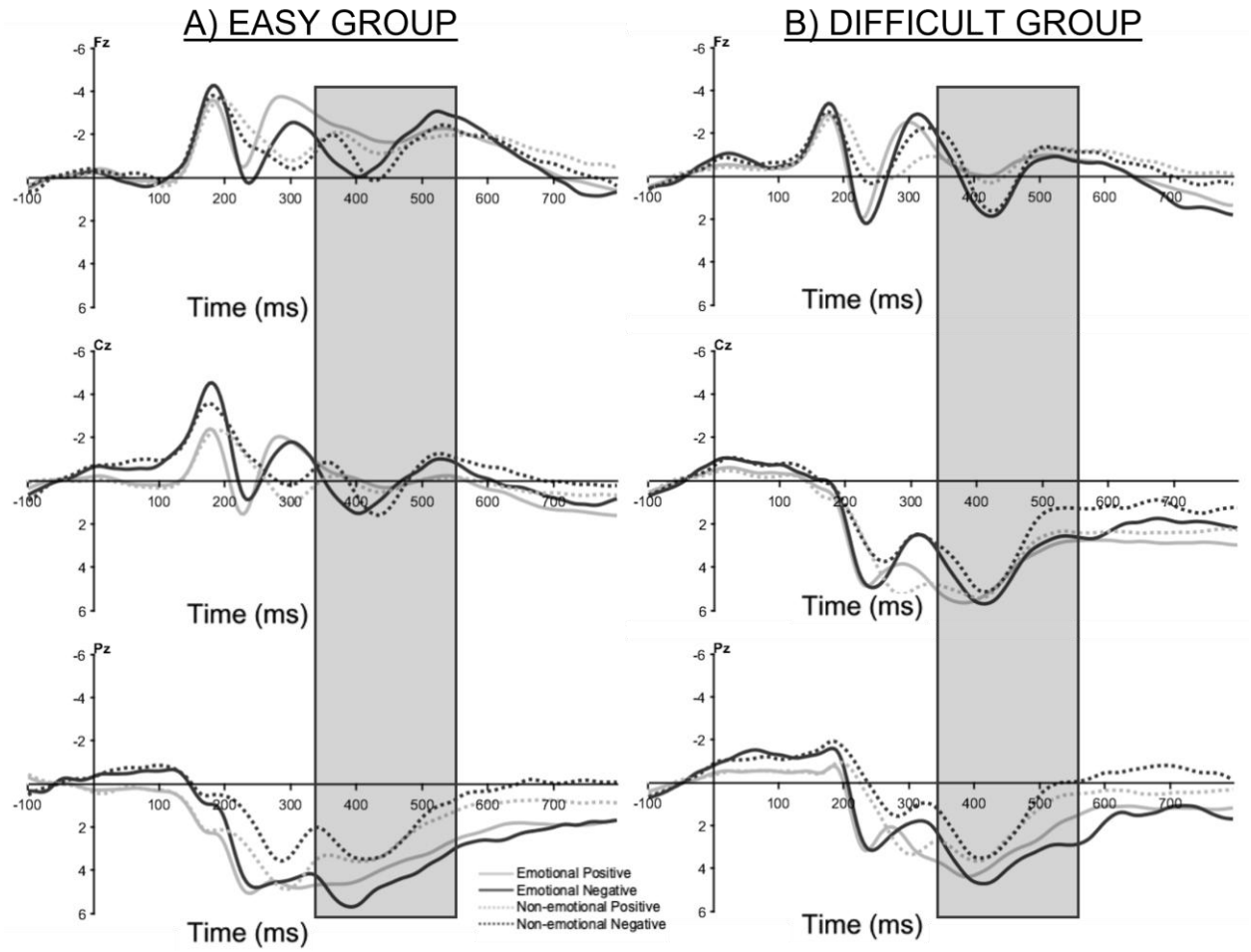
Mean P3b two-way interactions



Note. Graphical illustration of A) Task Difficulty x Channel, B) Feedback Condition x Channel, C) Valence x Channel.

Figure 3.7

ERP waveforms across three midline electrodes



Note. Feedback-locked ERP waveforms for easy and difficult group across three midline electrodes: Fz, Cz and Pz. The P3b time range is marked.

Resolving the interaction between Valence and Channel (see Figure 3.6C) revealed that negative feedback elicited a smaller mean P3b amplitude than positive feedback at channel Cz ($t(171)=-3.48$, $p<.001$) whereas no such differences were found at frontal or parietal areas (all p-values>.17). After negative feedback, the mean P3b amplitude was significantly larger at Pz vs. Cz ($t(171)=-3.63$, $p=.001$) and Cz vs. Fz ($t(171)=6.03$, $p<.001$), in contrast to positive feedback, for

which there was a larger P3b amplitude at Cz vs. Fz ($t(171)=12.1$, $p<.001$), but no significant amplitude differences for Cz vs. Pz ($p=.068$). No main effect of Task Difficulty ($p=.078$) nor an interaction between Task Difficulty and Feedback Condition ($p=.327$) was found. Figure 3.7 illustrates the mean P3b waveforms.

3.5 Discussion

We used a probabilistic learning task to investigate whether young adults' learning performance would benefit from emotional feedback during conditions with high working memory load. Additionally, we examined whether improved learning would be accompanied by improved detection of unexpected events and improved working memory updating following emotional feedback.

3.5.1 Learning Performance

Learning performance increased over the course of the experiment as reflected by increasing accuracy and decreasing reaction times. As expected, learning was worse in the difficult as compared to the easy task, indexed by lower accuracy and longer reaction times. As for the effect of emotional feedback, we found that accuracy was higher in the condition with emotional than non-emotional feedback for both groups. This leads us to suggest that different from our expectations, younger adults benefitted from emotional feedback under both working memory load conditions. This finding is in line with results of Hurlemann et al. (2010), where younger adults' learning performance was better after social feedback in a comparable task. This is partly explained by the social facilitation theory, which states that in well-learned tasks social stimuli may facilitate performance, while they inhibit performance in more demanding tasks (Geen & Gange, 1977). However, this would possibly have led to a disadvantage of emotional feedback under high

working memory load, which was not the case in our study. An alternative explanation could be the motivational relevance of the shown social stimuli and the direct comparison between emotional and non-emotional feedback in our study (Pfabigan & Han,2019; Sailer et al., 2023).

Our findings differ from a recent study by Ferdinand and Hilz (2020), who found no advantage of emotional feedback in an easy probabilistic learning task for younger adults. This discrepancy may be attributed to the use of neutral faces as feedback stimuli in their study, which potentially still elicited emotional (surprise) responses. Nonetheless, they demonstrated the benefits of emotional feedback for older individuals. One possible interpretation is that, unlike in older adults, where emotional feedback improves processing and compensates for age-related impairments, younger adults may require cognitive resources for processing additional emotional information. This is also supported by our reaction time data: Under low working memory load, participants benefitted from emotional feedback early in the experiment, while this advantage emerged later, after they had reached a certain level of proficiency, under high working memory load.

3.5.2 Feedback-related Negativity

We expected a greater advantage of emotional feedback under high working memory load; thus, we anticipated an increased peak-to-peak FRN in response to emotional as compared to non-emotional feedback, particularly in the difficult group. However, we did not find an interaction between feedback condition and task difficulty and no difficulty effect on the unsigned reward prediction error, that is reflected in the peak-to-peak FRN. These results are in contrast to Krigolson et al. (2015), who found a reduced detection of unexpected events during a condition with high working memory load, by adding a second task to a time estimation task (by telling participants

their eye movement will be recorded and that they would be evaluated on how well they performed).

This secondary task, however, might have had an effect not so much on working memory load, but instead might have added motivational significance to the task (Weinberg & Hajcak, 2010). In contrast, in our study, we aimed at increasing working memory load by increasing the number of stimulus-response associations, which - according to the behavioural difficulty effects - worked. Nevertheless, we could not find an effect of this manipulation on the peak-to-peak FRN amplitude, which corresponds to recent literature, according to which the FRN seems to be a rapid evaluation process which is not interfered with by higher working memory demands (Arbel et al., 2020; Ferdinand, 2019; Somon et al., 2019).

On the other hand, we found that emotional stimuli elicited enhanced feedback processing, as indicated by the fact that both groups, regardless of working memory load, demonstrated an increased FRN after emotional as compared to non-emotional information. This aligns with previous studies involving social stimuli, underscoring an augmented detection of expectancy violations in socioemotional contexts (Pfabigan et al., 2019; Pfabigan & Han, 2019; Schulreich et al., 2013). This heightened responsiveness may be attributed to the motivational significance and salience of social stimuli at a fundamental level (Weinberg & Hajcak, 2010). Motivational significance may even have been emphasized by the use of face feedback and the explicit mention that the facial expression would provide a performance evaluation. Our results differ from those of Ferdinand and Hilz (2020), who observed an enlarged FRN after non-emotional feedback compared to emotional feedback. Yet, it is crucial to note that their use of neutral faces in the non-emotional condition could have evoked larger expectancy violations due to their uncommonness and possibly negative connotation in everyday communication. With the inclusion of a non-

emotional condition that we tried to develop as similarly complex as the face stimuli, we were able to see this benefit also in younger adults. Additionally, we identified that negative feedback elicited a larger peak-to-peak FRN than positive feedback for both groups and both feedback conditions.

This aligns with common observations that negative feedback generates a larger FRN, explained by less expected negative feedback after having learned (Ferdinand, 2019; Ferdinand & Hilz, 2020; Holroyd & Coles, 2002; Pfabigan et al., 2019; Schulreich et al., 2013). Taken together, our findings indicate that the unsigned reward prediction error is not inherently sensitive to working memory load; rather, it is predominantly influenced by emotional information, which is likely due to the salience of the feedback received and the common observation that the FRN is generated by less expected (here negative) feedback when learning has taken place (Holroyd & Coles, 2002).

3.5.3 P3b

In our study, we additionally investigated working memory updating as reflected in the mean P3b amplitude. We hypothesized that especially under high working memory load, emotional feedback would lead to an enhanced working memory updating. Contrary to our expectations, we did not find an interaction between the emotionality of the feedback and higher working memory load. As for emotionality, we found a larger mean P3b amplitude at posterior electrode sites for emotional feedback (Martín, 2012; Polich, 2007). This result suggests that emotional feedback has a distinct impact on the neural processing of feedback by strengthening working memory updating processes, which are typically associated with the parietal P3b (Martín, 2012; Polich, 2007; Pfabigan et al., 2014, 2019; Schulreich et al., 2013). However, these results contrast the ones from Ferdinand & Hilz (2020), who could not find a benefit in working memory updating after emotional feedback in younger adults in a task that was similar to the easy condition.

A possible explanation could be a ceiling effect in the younger adults' sample in the previous study, which could have prevented an effect of emotionality to become visible. For task difficulty, we found that it did not change the size, but rather the topography of the P3b. Whereas the P3b showed a clear parietal maximum under low working memory load, it displayed a broader distribution, i.e., a parieto-central distribution under high working memory load. These different P3b topographies between the easy and difficult condition might suggest that task difficulty, here induced by manipulating working memory load, influences the neural mechanisms underlying attentional resource allocation during working memory updating.

The parietal P3b distribution observed in the easy group aligns with the characteristic topography typically found in tasks with moderate attentional demands, where parietal regions are engaged in context updating and stimulus evaluation processes (Ferdinand, 2019; Ferdinand & Hilz, 2020; Polich, 2007). This suggests that the P3b component plays a role in integrating incoming information into the existing cognitive context, and points to an efficient allocation of cognitive resources for the evaluation of feedback and the adjustment of behavior (Wurm et al., 2020). In contrast, the shift to a central P3b maximum in the difficult condition indicates an additional engagement of more central and frontal regions, which are usually associated with compensatory enhanced cognitive control processes (Ferdinand, 2019; Reuter-Lorenz et al., 2000; Segalowitz et al., 2001; Tregellas et al., 2006). The absence of a significant interaction between task difficulty and feedback condition suggests that the effects of higher working memory load and feedback condition on the P3b amplitude are largely independent. Emotional feedback leads to an enhanced working memory updating independently of working memory load. In contrast, a higher working memory load as induced by a higher task difficulty does not result in enhanced working

memory updating per se, but to an additional engagement of fronto-central networks becoming more engaged in difficult tasks to support increased cognitive control and attentional demands.

A third effect was that positive feedback elicited a larger P3b than negative feedback at central electrode sites. This might suggest that positive feedback has been harder to process and thus more frontal resources were needed for it to be processed adequately (cf. Ferdinand, 2019; Reuter-Lorenz et al., 2000; Tregellas et al., 2006; Segalowitz et al., 2001). A hint towards this interpretation can also be found in our exploratory analyses including Learning Half as a factor (see supplementary material). Here, we found that in the easy group, P3b amplitude at central and parietal electrode sites significantly decreased from the first to the second learning half for negative feedback, while this was not the case for positive feedback. This could indicate that negative feedback was not as difficult to process and probably also not as informative anymore after learning had taken place (Holroyd & Coles, 2002, Eppinger et al., 2008). However, these results should be interpreted with caution because of a low statistical power.

3.5.4 Limitations

We selected a between-subjects design due to the large number of trials necessary for reliable ERP analyses, to avoid participant exhaustion and practice effects which probably would have occurred in a within-subjects design. By restricting each participant to one condition, we sought to minimize these problems. However, we acknowledge that a between-subjects design has certain limitations, such as possible variability between groups and the need for larger sample sizes to achieve a statistical power comparable to that of within-subject designs. Despite these challenges, this approach was considered the most appropriate one for the study's objectives. Additionally, we included some measures to control for possible baseline differences in learning

ability and measures of crystallized and fluid intelligence between participant groups. An influential question in EEG research investigating feedback processing is the use of comparably complex feedback stimuli to rule out possible differences in feedback perception (Liu & Gehring, 2009; Pfabigan et al., 2019).

In the present study, we tried to reach this goal by contrasting emotional faces with scrambled images of the same faces. Our intention was to create non-emotional stimuli that still share critical aspects with faces, while eliminating emotional information. However, the scrambled images could still have been perceived as unusual and therefore might have influenced our results. Nevertheless, compared to Ferdinand and Hilz (2020), who used neutral face stimuli in the non-emotional condition, we obtained overall much smaller peak-to-peak FRNs in the non-emotional condition, which means that the present stimuli elicited smaller expectancy violations than neutral faces. This speaks in favor of our stimulus choice. Either way, future research should strive to create non-emotional stimuli that are even more comparable to emotional faces on all possible dimensions but emotionality. This idea can be supported by the ERP waveforms (especially in the easy group), in which non-emotional feedback elicited a delayed FRN. This could be due to the less effective discriminability of the scrambled faces, which we actually aimed to prevent by adding intuitive colors to emotional and non-emotional feedback. Faces are perceived as especially complex, but maybe the scrambled faces were perceived as even more complex stimuli, so participants needed more time to process adequately them. Future research therefore could try to manipulate the emotionality of the feedback stimuli by morphing images to a greater vs. lesser extent. By this, one could also avoid additional coloring of the faces to convey the valence of the feedback. Our choice to do use colour-coded feedback so introduced an additional perceptual cue in the emotional feedback condition, rendering the emotion of the faces irrelevant.

Nevertheless, significant effects of emotionality were still observed, suggesting that the presence of emotional content may have engaged additional cognitive processing and supported learning. In future research, a detailed investigation of the learning process over time and its possible modulation by emotional feedback would be interesting. This could be achieved through the joint modeling of behavioral and EEG data, which was beyond the scope of the present study. Also, due to the limited number of included trials (please see supplementary material), it was not possible to segment the EEG data into the same four bins as the behavioral data. For example, implementing a learning paradigm with a lower proportion of valid stimulus-response associations may help overcome these issues in future studies. With this approach, enough negative feedback trials could be included to perform a precise modeling approach to investigate the learning process.

Another concern regarding our FRN results that should be addressed is that of contamination by possible component overlap. More specifically, in the ERP waveforms right after feedback onset, a difference between positive and negative feedback is visible in the time range between 50 ms and 100 ms. Although an interval of 500ms between response and stimulus presentation is not uncommon for learning paradigms (Arbel et al., 2017; Arbel & Fox, 2021; Bellebaum & Daum, 2008; Eppinger et al., 2008, 2009; Ferdinand, 2019; Ferdinand & Hilz, 2020; Frank et al., 2005; Herbert et al., 2011; Weismüller & Bellebaum, 2016), we cannot exclude that this difference might reflect residual response-locked activity. It should be noted however, that the peak-to-peak quantification of the FRN that we used in our analyses should be robust to baseline differences and other differences in the ERP that occur before the P2, as this method of quantification uses the P2 peak as a baseline to measure the following N2 peak (Handy, 2005; Picton et al., 2000). Because this difference appears to not be present in the P2 time range any more, we think that the effects we found should still be reliable. Nevertheless, using a

deconvolution method to reduce the influence of possibly overlapping processing steps could be helpful for future studies (Ehinger & Dimigen, 2019).

3.5.5 Conclusion

Our study aimed at investigating whether emotional feedback could reduce learning deficiencies associated with higher working memory load in younger adults. Our findings revealed that during both working memory load conditions, younger adults showed improved performance after emotional feedback, suggesting that emotional feedback can support reinforcement learning. Additionally, the neural processes involved in feedback processing, the detection of unexpected events (as reflected in the peak-to-peak FRN) and working memory updating (as measured with the P3b) were strengthened by emotional feedback. A high working memory load led to decreased learning performance and supposedly the need to recruit more cognitive resources during working memory updating. However, the detection of unexpected events remained unaffected by increased working memory load. The unexpected lack of an interaction between emotionality and working memory load on the FRN and P3b suggests that these factors independently influence feedback processing.

4 Study 2: Age differences in socio-emotional feedback processing during learning: An ERP study

Authors: Braunwarth, Jana Isabelle[1]; Ferdinand, Nicola Kristina[1]

Affiliations: [1]Department of Psychology, University of Wuppertal, Germany

Journal: This manuscript was submitted for publication to the Journal *Frontiers in Aging Neuroscience* on 28th November 2025.

Status: Accepted for publication on 27th February 2026.

Acknowledgment: We gratefully acknowledge all participants for their time and commitment to this study. This study is part of JIB´s dissertation project.

Conflict of Interest: We declare no conflict of interest.

Author´s contributions: **JI Braunwarth:** Conceptualization, Data Curation, Formal Analysis, Methodology, Project Administration, Software, Validation, Visualization, Writing: Original Draft Preparation, Writing: Review & Editing; **NK Ferdinand:** Conceptualization, Funding Acquisition, Investigation, Methodology, Resources, Validation, Writing: Review & Editing, Supervision.

Published Preprint: https://doi.org/10.31234/osf.io/yxsd5_v2

Keywords: Feedback Processing, Feedback-Related Negativity (FRN), P3b, Socio-emotionality, Aging

4.1 Abstract

In an ever-changing environment, the ability to adapt behavior based on feedback is a crucial skill. Although this process is assumed to decline with age, initial evidence suggests that emotional information processing may help buffer against these age-related impairments. We therefore conducted a probabilistic learning task with emotional faces in two varying emotional intensities (weak vs. strong) to investigate whether healthy younger and older adults would benefit from strong emotional feedback during learning and whether these processes are reflected in feedback-related event related potentials (ERPs). *N* = 26 younger adults (mean age = 22.6, *SD* = 2.67 years) and *n* = 23 older adults (mean age = 71.9, *SD* = 3.60 years) took part in our study. Behavioral results showed that both age groups showed improved learning over time, but older adults particularly benefited from strong emotional feedback. ERPs revealed that the detection of unexpected events, reflected in the peak-to-peak FRN, was generally enhanced in older as compared to younger adults, possibly due to a generally enhanced motivational significance of socio-emotional stimuli. However, we could not find an effect of feedback condition for either group. Moreover, working memory updating, reflected in the P3b, was modulated by emotional intensity in older adults, showing increased updating after strong emotional negative feedback, whereas younger adults did not use strong emotional, but rather negative feedback to update their working memory.

4.2 Introduction

By 2050, one in six people worldwide will be over 65 years old (United Nations, 2023), highlighting the urgency of addressing cognitive aging. In line with this, investigating whether it is possible to reduce age-related learning deficits could help keep older adults engaged and active in society. While age-related declines in executive functions, memory, and reward-system

functioning are well established (Karrer et al., 2017; Salthouse, 2004), emotional processing appears relatively preserved, likely supported by neural mechanisms and a motivational shift toward emotionally meaningful information that together enhance the processing of emotional stimuli (Carstensen, 1991; Carstensen et al., 2006; Leclerc & Kensinger, 2008; Mather, 2012). However, it remains unclear to what extent socio-emotional feedback can lead to learning benefits and reduce age-related decline. This study therefore addresses this gap by examining the influence of socio-emotional feedback of varying intensities on learning in older adults, providing new insights into potential brain processes.

4.2.1 Learning from feedback

When learning through trial and error, mistakes provide feedback that allows us to adapt our behavior (Holroyd & Coles, 2002). Effective behavioral adjustment requires monitoring performance, detecting unexpected events, and updating working memory (Ullsperger, 2024). The medial prefrontal cortex (mPFC), particularly the dorsal anterior cingulate cortex (dACC), plays a key role in this process by integrating dopaminergic prediction error signals from the midbrain (Alexander & Brown, 2011; Cohen, 2008; Schultz, 2002). These processes can also be indexed in feedback-locked ERPs using an electroencephalogram (EEG).

These processes can also be indexed in feedback-locked ERPs. The feedback-related negativity (FRN) is a frontocentral negative deflection around 200–300 ms after feedback, typically generated in the dACC (Miltner et al., 1997; Walsh & Anderson, 2012). It has been interpreted as reflecting the monitoring of outcome salience or unexpectedness, representing an unsigned reward prediction error (Ferdinand et al., 2012; Oliveira et al., 2007; Paul et al., 2025; Pfabigan et al., 2011; Talmi et al., 2013). This interpretation is supported by fMRI findings of increased ACC

activation for unexpected compared to expected events (Braver et al., 2001; Ferdinand & Opitz, 2014; Wessel et al., 2012). Other accounts conceptualize the FRN as a signed reward prediction error, specifically signaling outcomes that are worse than expected (Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Sambrook & Goslin, 2014). More recent work additionally highlights the reward positivity (RewP), linked to enhanced processing of positive outcomes (Holroyd et al., 2008b; Proudfit, 2015). Overall, the FRN is shaped by several feedback factors, including negative valence, magnitude, expectancy, and timing (Kirsch et al., 2022; Martín, 2012; Opitz et al., 2011; Severo et al., 2020; Yeung et al., 2004). In line with this, the present study adopts the expectancy-violation framework, interpreting the FRN as an index of neural sensitivity to unexpected events.

After this initial monitoring stage, a subsequent process facilitates behavioral adaptation by updating working memory. In the ERP, this step is indexed by the P3b, a positive component peaking around 350–500 ms after feedback presentation with a maximum at parietocentral sites (Donchin & Coles, 1988; Martín, 2012; McCarthy & Donchin, 1981; Polich, 2007). The P3b is known to be sensitive to the frequency of events, as well as task complexity and task relevance. Specifically it means that P3b amplitudes are enhanced for rare, unexpected, or behaviorally relevant stimuli, and are further shaped by working memory load, decision uncertainty, and the requirement to update task representations, thereby underscoring the function of the P3b as a marker of contextual updating (Bellebaum & Daum, 2008; Berg et al., 2019; Ferdinand et al., 2012; Mecklinger et al., 1994; Paul et al., 2025; Severo et al., 2020; Ullsperger et al., 2014). This contextual updating has been shown to be enhanced after negative valence in probabilistic learning tasks, suggesting that negative feedback is more relevant to perform these tasks successfully (Ferdinand, 2019; Ferdinand & Hilz, 2020; Frank et al., 2005; Kamp et al., 2024).

4.2.2 Age-related alterations in learning from feedback

Aging is associated with changes in neural systems, including a decline in dopaminergic neurons that support performance monitoring and behavioral adaptation (Bäckman et al., 2000; Bäckman et al., 2006; Karrer et al., 2017; Nieuwenhuis et al., 2005; Schultz, 2002; Ullsperger, 2024). This decline is characterized by reduced receptor density, firing efficiency, and dopamine availability in regions such as the prefrontal cortex and striatum (Bäckman & Farde, 2005; Collier et al., 2011; Lighthall et al., 2018; Wild-Wall et al., 2009). Correspondingly, feedback-learning studies show that older adults are less efficient at detecting unexpected events, as reflected in smaller FRN amplitudes and reduced differentiation between positive and negative feedback compared to younger adults (Bellebaum et al., 2011; Eppinger et al., 2008; Ferdinand, 2019; Ferdinand & Kray, 2013; Hämmerer et al., 2011; Herbert et al., 2011; Nieuwenhuis et al., 2005; Pietschmann et al., 2011; West & Huet, 2020).

Regarding working memory updating, P3b amplitudes decrease with age, particularly in non-learning tasks such as oddball or task-switching paradigms (Friedman et al., 2007; Gajewski et al., 2018). Although this reduction is typically interpreted as reflecting age-related decline in updating processes, findings from feedback-learning tasks are mixed: some studies report preserved P3b amplitudes in older adults (Fernandes et al., 2018; West & Huet, 2020), whereas others observe reduced amplitudes (Daffner et al., 2011; Gajewski & Falkenstein, 2014; Polich & Criado, 2006; Wild-Wall et al., 2009). These inconsistencies may be partly explained by task characteristics, such as task complexity and the reliance on strategic updating (e.g., focusing on the most relevant feedback; Ferdinand & Kray, 2013; Gaál & Czigler, 2015).

Moreover, the literature consistently reports topographical changes, attributed to reduced working memory capacity in older adults and compensatory recruitment of frontal resources, with younger adults showing a parietal activation and older adults displaying a more broadly distributed topography including frontal activation (Cabeza et al., 2002; Daffner et al., 2011; Ferdinand, 2019; Ferdinand & Hilz, 2020; Friedman et al., 1997; Lubitz et al., 2017; Pietschmann et al., 2011; Reuter-Lorenz et al., 2000; Schmitt et al., 2014a, 2014b; Tregellas et al., 2006; Wild-Wall et al., 2009).

These neurophysiological changes are also reflected in observable behavioral patterns with increased error rates and slower reaction times compared to younger adults (Eppinger et al., 2008; Ferdinand, 2019; Lighthall et al., 2018; Mell et al., 2005; Pietschmann et al., 2011; Wild-Wall et al., 2009). In sum, there is much evidence of changes that appear to impair the efficient processing of feedback, thereby limiting behavioral adaptation in learning from feedback in older adults.

4.2.3 Impact of emotion on learning from feedback

Although cognitive decline is a hallmark of aging, socio-emotional processing seems to remain largely intact. Behavioral findings suggest that older adults perceive and respond to socio-emotional stimuli much like younger adults, indicating that these functions are comparatively resilient to age-related decline (Carstensen et al., 2006; Ferdinand et al., 2018; Ferdinand & Czernochowski, 2018; Kensinger & Gutchess, 2017). Two complementary mechanisms have been proposed to account for this relative preservation. First, neuroimaging studies indicate that key neural systems involved in socio-emotional processing, such as the amygdala and insula, undergo comparatively little structural or functional decline with age (Leclerc & Kensinger, 2008; Mather, 2012). Second, motivational theories of aging, e.g., the socio-emotional selectivity theory

(Carstensen, 1991; Carstensen et al., 2006) or the Strength and Vulnerability Integration (SAVI) model (Charles, 2010; Charles & Luong, 2013; Charles & Piazza, 2024), suggest that aging is accompanied by a motivational shift which includes maintaining a positive emotion regulation balance and investing in emotionally meaningful social interactions. To achieve this, a focus on processing socio-emotional stimuli is crucial. Together, these factors suggest that socio-emotional feedback may be particularly effective in supporting learning from feedback in older adults.

In line with these considerations, studies with older adults have shown that positive socio-emotional feedback (happy faces) can enhance performance under low task complexity, whereas negative feedback (angry faces) impairs learning when complexity is high (Gorlick et al., 2013). However, when socio-emotional feedback was compared to monetary feedback, no additional benefit of emotional feedback was found (Nashiro et al., 2011).

To our knowledge, the only study examining the electrophysiological correlates of learning from socio-emotional feedback in older adults was performed by Ferdinand and Hilz (2020), who examined whether socio-emotional feedback modulates learning performance and neural feedback processing in younger and older adults. In a probabilistic learning task, participants received either socio-emotional (happy vs. disgusted) or neutral facial feedback (background color indicating correct vs. incorrect responses). Older adults learned better when socio-emotional feedback was provided, likely because negative feedback in this condition triggered stronger working memory updating, as reflected in enhanced P3b amplitudes compared to neutral feedback. No modulation of the FRN by socio-emotional feedback was found. However, this study contained some limitations. First, ERP analyses revealed enhanced FRN peak-to-peak amplitudes after neutral feedback, suggesting that this type of feedback induced large expectancy violations. This raises the question of whether neutral faces are an appropriate choice for non-emotional stimuli, given their

atypicality and potential negative connotation in everyday social interactions. Moreover, in this study, the neutral expressions were presented on blue or yellow backgrounds to signal correct or incorrect feedback (randomized across participants). This design likely added working memory demands in the neutral condition, as participants had to remember the color–feedback associations to be able to learn. Both limitations could have caused worse learning rates and affected the ERPs in the neutral feedback condition. Thus, it is not clear whether the results reflect a processing benefit for socio-emotional feedback or a processing disadvantage in the neutral feedback condition (Ferdinand & Hilz, 2020).

In contrast, findings for younger adults do not consistently show improvements after socio-emotional feedback. Hurlemann et al. (2010) investigated facilitation of declarative learning after social relative to non-social stimuli (faces vs. lights). Social feedback (thumps vs. signs) further elicited larger FRN and P3b responses and improved time-estimation accuracy by Pfabigan et al. (2019). In contrast, Ferdinand and Hilz (2020) reported no advantage for younger adults neither on a behavioral nor on a neural level in a probabilistic learning task, possibly due to ceiling effects in the learning task (Ferdinand & Hilz, 2020).

Another study by Braunwarth and Ferdinand (2025) therefore manipulated task complexity by increasing working memory load in younger adults and found that socio-emotional feedback facilitated performance in the difficult task after initial task knowledge was acquired. Socio-emotional compared to non-emotional feedback enhanced detection of unexpected events (larger FRN) and working memory updating (larger P3b), irrespective of task complexity, indicating increased sensitivity to socio-emotional feedback (Braunwarth & Ferdinand, 2025).

In conclusion, while some advantages of socio-emotional feedback in older adults are evident, the challenge of defining a suitable "neutral" feedback condition remains, leaving the full extent of these benefits unclear and contributing to the mixed findings within age groups so far.

4.2.4 The present study

With the present study, we aim to add understanding on how socio-emotional feedback can support learning performance as well as monitoring processes and working memory updating in younger and older adults. Similar to Ferdinand and Hilz (2020), we used a probabilistic learning task, in which stimulus-response associations had to be learned via feedback. To address the limitations of neutral feedback discussed above, we used weak vs. strong emotional feedback. This way, the feedback stimuli became more comparable, and we did not need to use color to signal feedback valence.

We assumed that younger adults would learn faster, reflected in a steeper increase in accuracy and decrease in reaction times across the experiment, and would reach overall higher learning rates than older adults. Based on previous findings, we expected ERP effects related to the detection of unexpected events and working memory updating to be primarily driven by negative feedback, thereby replicating previously reported feedback-related ERP modulations. Further, we expected that older adults would show less efficient detection of unexpected events, indicated by smaller peak-to-peak FRN amplitudes compared to younger adults, and reduced working-memory updating, indicated by smaller mean P3b amplitudes. However, we assumed that particularly older adults would benefit from strong emotional feedback during learning, as reflected in higher accuracy and faster reaction times in this condition compared to the weak emotional condition. In addition, we expected that detection of expectancy violations (FRN) and working-memory

updating (P3b) would be enhanced following strong emotional feedback. Finally, we hypothesized that older adults would show stronger frontal activation of the P3b relative to younger adults, reflecting increased compensatory updating demands, particularly for weak compared to strong emotional feedback.

4.3 Methods

4.3.1 Participants

Prior to conducting the experiment, we used G*power (Faul et al., 2007) to estimate the minimum sample size using a power of *f*= .8, a small to middle-sized effect size of .15, which was based on earlier studies (Braunwarth & Ferdinand, 2025; Ferdinand & Hilz, 2020), and an α-level of .05. This analysis revealed a minimum of 18 participants for each group for our largest hypothesized interaction. Taking possible drop-outs into consideration, we aimed to recruit a minimum of 25 younger (aged 19-29 years) and 25 older adults (aged 67-80 years). Participants were recruited through social media and the SONA recruiting system at the University of Wuppertal. Older adults were further recruited using flyers distributed in local institutions, sports clubs, and cultural facilities. Participants either received course credit or 10€/h expense allowance. Inclusion criteria were right handedness, no psychiatric or neurological diseases, no pacemakers or cochlear implants, and normal or corrected-to-normal vision. Older adults additionally completed the Mini-Mental State Examination (MMSE) and were included in the study only if they achieved a score > 27 (Salis et al., 2023), ensuring the absence of cognitive impairment. Four older and two younger participants were excluded from the final sample due to EEG data with more than 25% artifactual trials, visual impairments, or insufficient understanding of the task requirements.

Participants were also tested on the Digit Symbol Substitution Test (DSST; adapted from Wechsler, Jaeger, 2018) and the Multiple choice vocabulary test (MWT-B; adapted from Lehrl, 2005) to assess fluid and crystallized intelligence, respectively. Younger adults outperformed older adults on the DSST ($t(47) = -6.76$; $p < .001$, two-tailed), while older adults obtained higher values in the MWT-B ($t(46) = 8.39$; $p < .001$, two-tailed). These findings match the idea of declining fluid and preserved crystallized intelligence with increasing age (Baltes & Lindenberger, 1999).

Table 4.1

Group Demographics

	Older adults	Younger adults
Age	71.6 (3.6)	22.6 (2.7)
Sex n (male/female/divers)	9/14/0	13/13/0
First language	German (n = 23)	German (n = 22) Farsi (n = 2) Arabic (n.s.) (n = 1) Moroccan arabic (n = 1)
MWT Score	27.6 (3.1)	20 (3.1)
DSST Score	41.5 (8.8)	60.7 (10.9)

Note. MWT = Multiple Choice Vocabulary Test, DSST = Digit Symbol Substitution Test. Values are means with standard deviations in parentheses where applicable. N.s. = not specified.

We followed the Declaration of Helsinki and the study was approved by the ethics committee of the University of Wuppertal. All participants signed informed consent before participation. An overview of the final sample can be found in Table 1.

4.3.2 Task and Stimuli

In the present study, participants completed a probabilistic learning task (adapted from Ferdinand & Hilz, 2020), in which they learned a stimulus-response association by pressing a button, followed by feedback (see Figure 4.1). The stimuli consisted of different object groups (e.g., clothing, fruits, animals) and were taken from a standardized object database (Rossion & Pourtois, 2004). Each object had a size of 281x197 or 197x281 pixel and was either linked to weak or strong emotional feedback.

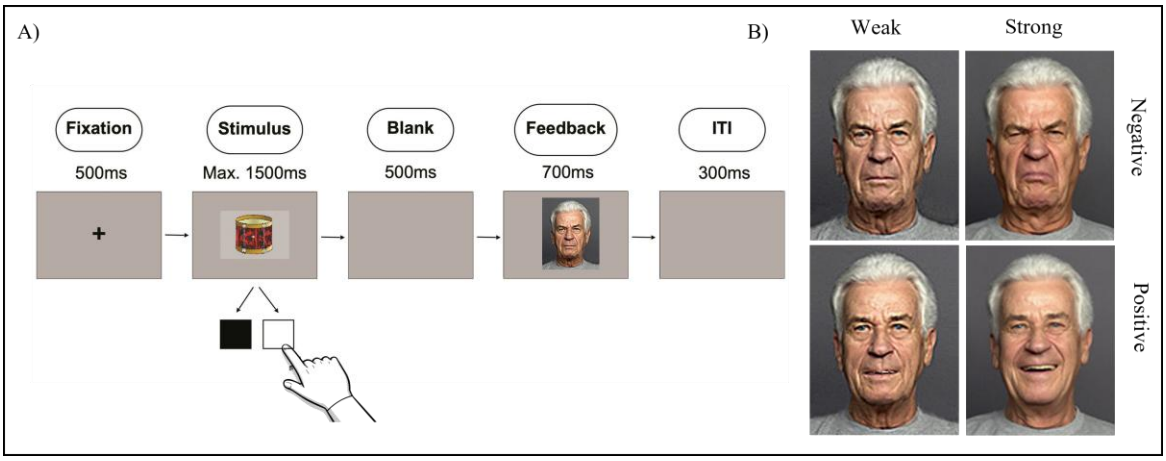
The feedback stimuli were taken from the FACES database (Ebner et al., 2010) with a size of 112x140 pixel. The emotional feedback condition consisted of happy faces for positive and disgusted faces for negative feedback, as the ability to recognize those two emotions seems to remain relatively intact as people age (Orgeta & Phillips, 2007; Ruffman et al., 2008).

For the weak emotional feedback, the same faces as in the strong emotional condition were used. To reduce emotional intensity, these images were morphed with neutral faces from the same database using Fantamorph Version 5.0 (FantaMorph, Abrosoft: http://www.fantamorph.com/). To identify the most suitable morph level, we conducted a pre-study with N = 69 participants (M = 24.39 years, SD = 6.73), in which ten different morph levels were rated with respect to perceived emotionality. The aim was to select images that were clearly distinguished from neutral stimuli, but at the same time contained significantly less emotion than the strong emotional images. Based on these ratings, the weak emotional stimuli were defined as those representing the lowest morph level that was still perceived as emotional and significantly different from the strong condition. As a result, a morph level of 40% emotional face (happy or disgust) and 60% neutral face was identified for both valences and used as weak emotional feedback in the main study. To address

potential biases related to age and gender, four distinct persons were used for face stimuli, including a young man, young woman, old man, and old woman, presented in a counterbalanced order across all participants (all four of them were included in the pre-study). All facial stimuli presented were White. Images were presented on a grayscale background and an example image can be found in Figure 4.1.

Figure 4.1

Trial procedure and feedback stimuli



Note. A) Representative trial procedure depicting weak negative emotional feedback. B) Morphed weak and strong emotional feedback for the older man, illustrated across both valences.

In the probabilistic learning task, participants were instructed to act as moving helpers, deciding whether objects had to be loaded in a black or a white truck. Colored response keys on the keyboard ("c" for black, "m" for white) were used for item allocation and participants received feedback from their boss based on their responses. To avoid one-trial learning, 10% of the received feedback was invalid, resulting in positive feedback after incorrect responses and negative feedback after correct responses.

Before the main experiment started, all participants completed eight practice trials, with the option to repeat if necessary. The experiment consisted of 720 trials, which were divided into four learning blocks. Each learning block consisted of 180 trials in which the same six objects of an object category had to be allocated to one of the two keys. Short breaks were provided every 60 trials, with participants determining their duration. After each learning block, we included a short retrieval task asking about the assignment of the objects by showing every object again and asking the participants to press the correct button.

At the start of a trial, a fixation cross appeared for 500ms followed by an object starting with a maximum response window of 1000ms in the first trial. To counteract age and individual differences in the speed of the task, the maximum response time was adapted (in the range of 600-1500ms) based on participant´s timeouts. In case of exceeding the response window, participants received a message on the screen saying “zu langsam” (German for “too slow”). Participants who did not exceed the time range within 20 trials received a response time of 100ms less for the next 20 trials. If they exceeded the time once in these trials, the time range remained the same for the next 20 trials. In case of exceeding the time window more than once, they were given 100ms more in the next 20 trials. Afterwards, a blank screen appeared for 500ms and then the feedback was shown for 700ms followed by an intertrial interval of 300ms (see Figure 4.1).

4.3.3 Procedure

Upon arrival, participants signed informed consent. Older adults underwent the MMSE (Folstein et al., 1975) and both groups right-handedness was assessed using the LQ-Questionnaire (Oldfield, 1971). They then completed the Digit Symbol Substitution Test (Jaeger, 2018) as a measure of fluid intelligence and a demographic questionnaire covering education, exercise,

nutrition, and social participation. Additional questionnaires included assessments of emotion regulation (Abler & Kessler, 2011) and the German version of the Interpersonal Reactivity Index (Paulus, 2009). Participants also completed a digital version of the german MWT-B to measure crystallized intelligence (Lehrl, 2005). After EEG preparation, the probabilistic learning task was presented on a 27 inch screen in an electrically shielded sound proof EEG cabin. Afterwards, participants answered follow-up questions on sleep, concentration, and learning strategies before receiving expense allowances and departing.

4.3.4 EEG Recording and Analysis

While EEG was recorded using BrainVision Recorder 2.0 (BrainVision Recorder, Version 1.23.0003, Brain Products GmbH, Gilching, Germany), the experimental paradigm was presented by E-Prime 3.0 (Psychology Software Tools, Pittsburgh, PA). 58 active silver/ silver chloride electrodes were attached according to the international 10-20 system (Jasper, 1958). The ground electrode was placed at position AFz and the left mastoid served as online reference electrode. An electrooculogram (EOG) was recorded for offline eye movement correction. For this purpose, electrodes were placed supra- and infraorbitally to the right eye and near the outer canthi of both eyes. All impedances were kept below 20kΩ. The EEG and EOG signal were filtered online using a low pass filter (250 Hz) and digitized with a sampling rate of 500 Hz. Offline processing was performed using Matlab R2023 (The Mathworks Inc., 2022) and the eeglab toolbox v.2021.1 (Delorme & Makeig, 2004). A high pass filter of 0.01Hz and a low pass filter of 30Hz were applied to the EEG data. Furthermore, EEG data were referenced to linked mastoids and downsampled to a sampling rate of 250Hz. Afterwards, an independent component analysis was performed to remove eye blinks and other artefactual components, which then were removed semi manually using IClabel (Pion-Tonachini et al., 2019) and visual inspection. After removal, epochs with a

time frame of 900ms for the relevant segments (strong emotional positive, strong emotional negative, weak emotional positive, weak emotional negative) were cut with a pre-stimulus baseline of -100ms before feedback presentation using ERPlab v8.30 (Lopez-Calderon & Luck, 2014). Epochs exceeding 75 μV were removed in an artifact rejection step.

We calculated the peak-to-peak FRN by subtracting the positivity in the P2 time window from the negativity in the N2 time window at channel FCz (Ferdinand, 2019; Ferdinand & Hilz, 2020; Gheza et al., 2018; Paul et al., 2020). In line with the literature, we used slightly different time windows for younger and older adults to catch the peaks adequately (Luck & Gaspelin, 2017). Therefore, we used the negativity in a time window of 230ms to 330ms and the positivity in a time window of 170ms to 230ms for younger adults and the negativity between 240ms and 340ms and the positivity between 180ms to 240ms post feedback presentation for older adults. For both participant groups, the P3b was defined as the mean amplitude between 350–550ms after feedback (Martín, 2012; Polich, 2007). In order to investigate potential age-related frontal shifts in the distribution of P3b activity, the component was analyzed at three midline electrode positions: Fz, Cz, and Pz.

4.3.5 Data analysis

To assess learning performance, we performed mixed ANOVAs with Age (young, old) as between-subject factor and Feedback Condition (strong emotional, weak emotional) and Learning Block (1,2,3,4) as within-subject factors on accuracy and reaction times as dependent variables. For all behavioral analyses, trials with reaction times < 100ms were excluded. The analysis of reaction times further included only correct trials. Significant effects involving the factor Learning Block were followed up with pairwise comparisons between adjacent quarters (LB1 vs. LB2, LB2

vs. LB3, and LB3 vs. LB4) in order to limit the number of comparisons and maintain interpretability.

ERP analyses were carried out using a mixed-repeated measures ANOVA with Age (young, old) as the between-subject factor, and Feedback Condition (strong emotional, weak emotional) and Valence (positive, negative) as within-subject factors. To be able to examine topographical differences in the P3b, the factor and Channel (Fz, Cz, Pz) was additionally included in this analysis. To reduce the number of comparisons, it was entered into the ANOVA as a repeated contrast (Fz vs. Cz, Cz vs. Pz).

Even though we did not have an explicit hypothesis about the ERP change over time, we included an additional factor Learning Half (1,2) for the FRN post-hoc analysis, because a main effect of valence was not revealed in the original analysis, contradicting empirical evidence (Eppinger et al., 2008; Holroyd & Coles, 2002; Wurm et al., 2020). While the behavioral data were split into quarters, there were not enough trials to divide the ERP data in the same manner; therefore, the ERP data were split into halves. For younger adults, the mean number of included trials for strong emotional positive feedback was 130.73 (*SD* = 17.68) in the first learning half and 145.46 (*SD* = 11.88) in the second learning half. For strong emotional negative feedback, the corresponding means were 25.50 (*SD* = 12.09) and 12.96 (*SD* = 12.50). In the weak emotional condition, mean included trials for positive feedback were 116.46 (*SD* = 17.66) in the first learning half and 139.57 (*SD* = 16.72) in the second learning half, whereas mean included trials for negative feedback were 36.57 (*SD* = 17.76) and 18.62 (*SD* = 13.05), respectively. For older adults, the mean number of included trials for strong emotional positive feedback was 114.10 (*SD* = 16.66) in the first learning half and 135 (*SD* = 17.85) in the second learning half. For strong emotional negative feedback, mean included trials were 35.35 (*SD* = 14.79) and 21 (*SD* = 16.32). In the weak emotional

condition, mean included trials for positive feedback were 92.04 (*SD* = 29.34) and 101.26 (*SD* = 27.38) for the first and second learning half, respectively, and mean included trials for negative feedback were 59.17 (*SD* = 18.88) and 49.48 (*SD* = 27.02). However, the trial numbers for negative feedback are low, thus the results should be interpreted with caution.

For all statistical analyses, results were reported following a hierarchical approach. Specifically, when higher-order interactions involving a given factor were statistically significant, lower-order effects (i.e., main effects or lower-order interactions including the same factor) were only reported if they were not contradicted by these higher-order interactions. In cases were higher-order effects contradicted lower-order effects, only the more informative higher-order effects, followed by targeted follow-up analyses to clarify the nature of these interactions, were described. Accordingly, only those effects that remained interpretable in the absence of conflicting higher-order interactions are described. This reporting strategy was applied consistently across all analyses to ensure a clear and coherent interpretation of the results.

If necessary, Greenhouse-Geisser corrections were applied to adjust for sphericity violations, and epsilon-corrected p-values with uncorrected degrees of freedom are reported. For ANOVAs, we report partial eta squared as an effect size. Bonferroni corrections were used for post-hoc tests, and Cohen's d is reported for pairwise comparisons. The significance level was set to $\alpha = .05$ for all analyses, which were conducted in RStudio (Version 4.3.2; R Core Team).

4.4 Results

4.4.1 Behavioral Data

4.4.1.1 Accuracies. The analysis of the relative frequencies of correct responses revealed a main effect of Learning Block ($F(3,141)=169.36$, $p<.001$, $\eta_p^2 = .78$), indicating increasing accuracy over time, and a main effect of Feedback Condition ($F(1,47)=75.32$, $p<.001$, $\eta_p^2 = .62$), revealing better learning after strong than weak emotional feedback. In addition, there was a main effect of Age ($F(1,47)= 19.88$, $p<.001$, $\eta_p^2=.30$), that was qualified by interactions with Feedback Condition ($F(1,47)=21.32$, $p<.001$, $\eta_p^2 =.31$) and Learning Block and Feedback Condition ($F(3,141)=5.14$, $p = .002$, $\eta_p^2 = .10$) were found.

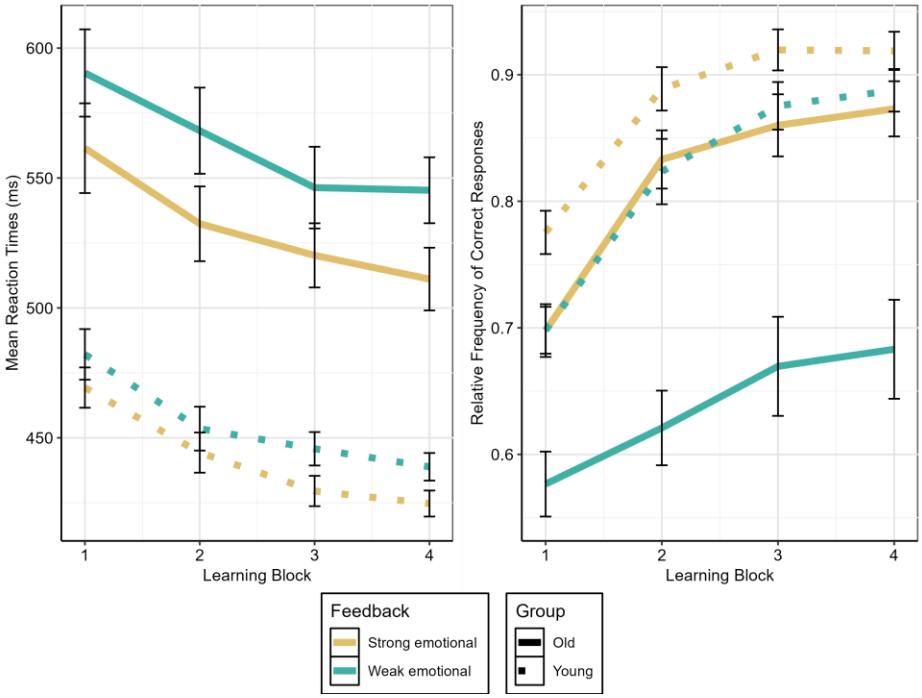
To resolve the three-way interaction, pairwise comparisons between adjacent learning blocks were conducted separately for each combination of Age and Feedback Condition. In younger adults, accuracy significantly increased from LB1 to LB3 after strong as well as weak emotional feedback (strong emotional: LB1 vs. LB2: $t(25)= –8.94$, $p<.001$, $d= –1.75$; LB2 vs. LB3 ($t(25)= –2.97$, $p=.006$, $d=–0.58$; LB3 vs. LB4: $p=.922$; weak emotional: LB1 vs. LB2 $t(25)= –10.20$, $p<.001$, $d= –2.00$; LB2 vs. LB3 ($t(25)= –3.82$, $p<.001$, $d=–0.75$; LB3 vs. LB4: $p=.234$). In older adults, the same pattern was found (strong emotional: LB1 vs. LB2: $t(22)= –10.02$, $p<.001$,$d= –2.09$; LB2 vs. LB3: $t(22)= –2.30$, $p=.032$, $d= –0.48$; LB3 vs. LB4: $p=.408$; weak emotional: LB1 vs. LB2: $t(22)=–2.20$, $p=.039$, $d=–0.46$; LB2 vs. LB3: $t(22)=–2.28$, $p=.033$, $d=–0.48$; LB3 vs. LB4: $p=.502$).

To explore age-related differences underlying the present three-way interaction, we examined accuracy across learning blocks (please see Figure 4.2). After strong emotional feedback, younger adults showed significantly higher accuracies than older adults in LB1 ($t(44) = −2.88$, $p =$

.006, *d* = -0.83). In contrast, age differences did not reach statistical significance in LB2, LB3 or LB4 (all *p*-values >.050). In the weak emotional feedback condition, younger adults consistently outperformed older adults across all learning blocks (LB1: $t(41.1) = -3.84$, $p < .001$, d = -1.11; LB2: $t(45.3) = -5.17$, $p < .001$, d =-1.48; LB3: $t(31.8) = -4.74$, $p < .001$, d = -1.38; LB4: $t(30) = -4.81$, $p < .001$, d = -1.40, see Figure 4.2).

Figure 4.2

Mean reaction times and relative frequency of correct responses



Note. Mean reaction times and relative frequency of correct responses for both groups and both feedback conditions across four learning blocks (whiskers denote standard error of the mean).

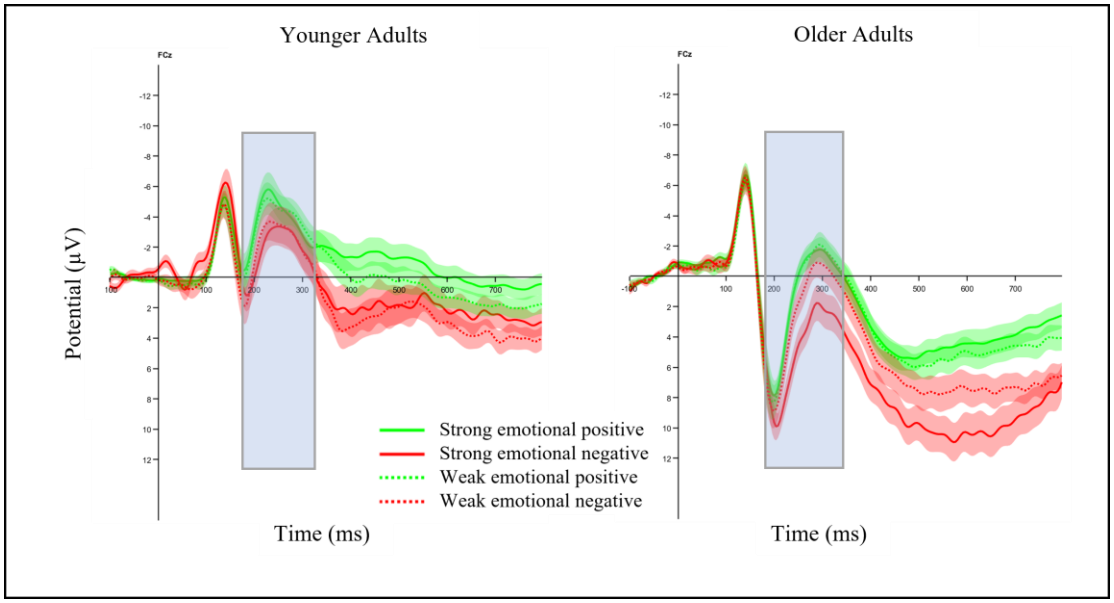
4.4.1.2 Reaction Times. The ANOVA on reaction times revealed a main effect of Age, with younger adults having faster reaction times than older adults ($F(1,47)=46.68$, $p<.001$, $\eta_p^2=.49$), and a main effect of Learning Block ($F(3,141)= 42.07$, $p<.001$, $\eta_p^2=.47$), with decreasing reaction times from LB1 to LB4 (LB1 vs. LB2: ($t(97)= 7.79$, $p<.001$, $d=.78$; LB2 vs. LB3: $t(97)= 5.11$, $p<.001$, $d=.52$; LB3 vs. LB4: $t(97)=2.23$, $p=.028$, $d=.23$). Additionally, a main effect of Feedback Condition ($F(1,47)= 64.95$, $p<.001$, $\eta_p^2=.58$) and an interaction between Age and Feedback Condition ($F(1,47)= 10.88$, $p=.002$, $\eta_p^2= .19$) were revealed. Resolving the interaction resulted in both age groups having significantly faster reaction times after strong than weak emotional feedback (older adults: $t(91)=-8.58$, $p<.001$, $d=.89$; younger adults: $t(103)=-6.63$, $p<.001$, $d=.65$), with a larger effect size for older than younger adults (see Figure 4.2).

4.4.2 Electrophysiological Data

4.4.2.1 Peak-to-Peak FRN. The peak-to-peak FRN ANOVA model yielded an effect of Age, with older adults exhibiting a larger peak-to-peak FRN than younger adults ($F(1,47)=16.15$, $p<.001$, $\eta_p^2 = .25$, see Figures 4.3 and 4.4). No other effects reached significance. Importantly, neither a significant main effect for Feedback Condition ($p=.058$) nor significant interactions with this factor were found (all p-values>.09).

Figure 4.3

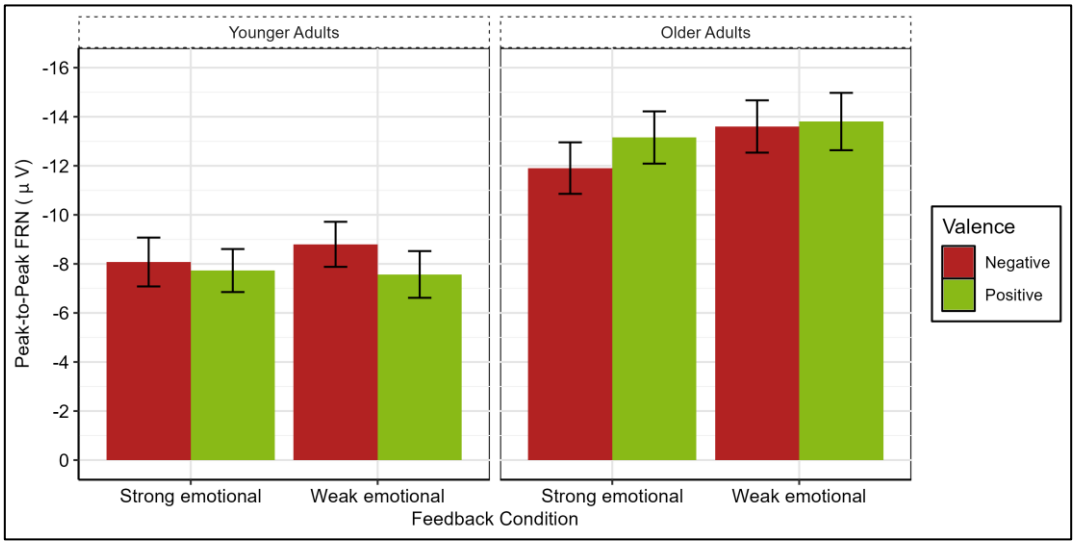
Feedback-locked ERP waveforms at channel FCz



Note. Peak-to-peak FRN time range is marked and shaded error bands, representing the standard error of mean, are shown.

Figure 4.4

Bar plot illustrating the size of the peak-to-peak FRN



Note. Error bars denote standard error of the mean.

To better understand the absence of the typical FRN valence effect, we conducted post-hoc analyses by splitting the experiment into halves and including this factor in the mixed ANOVA. Doing so revealed again the main effect of Age ($F(1,47)= 12.77$, $p<.001$, $\eta_p^2 =.21$), an interaction between Age and Valence ($F(1,47)= 7.80$, $p=.008$, $\eta_p^2 =.13$), and Age, Valence and Learning Half ($F(1,47)= 21.18$, $p<.001$, $\eta_p^2=.31$).

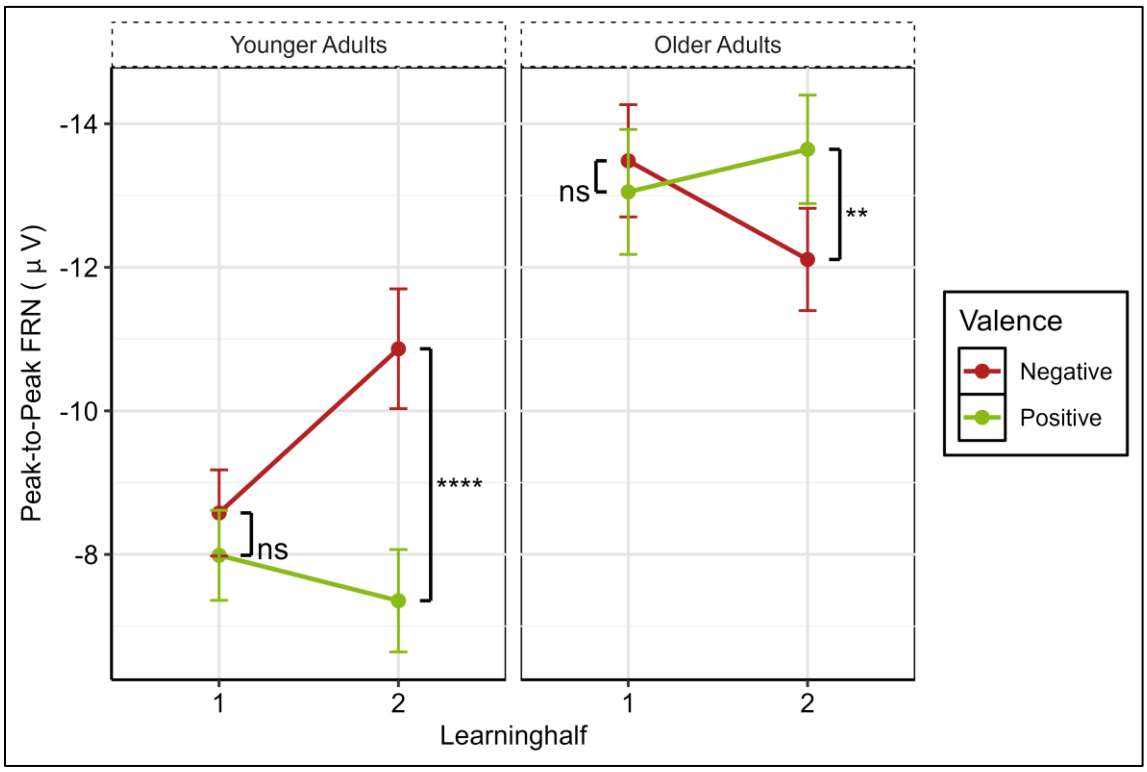
Post-hoc comparisons revealed age-related differences in FRN amplitudes that varied as a function of Valence and Learning Half (please see Figure 4.5). During the first learning half, older adults showed significantly larger FRN amplitudes than younger adults following both negative feedback ($t(87)= -4.98$, $p< .001$, $d= -1.01$), and positive feedback ($t(83.9)= -4.72$, $p< .001$, $d= -0.96$). In the second learning half, no significant age difference was observed for negative feedback ($p= .26$). In contrast, for positive feedback, older adults continued to exhibit significantly larger FRN amplitudes than younger adults ($t(94.6)= -6.05$, $p< .001$, $d= -1.22$). Further, we examined changes in peak-to-peak FRN amplitudes from Learning Half 1 to Learning Half 2 separately for each Age Group and Valence.

In older adults, FRN amplitudes were significantly larger in Learning Half 1 than in Learning Half 2 following negative feedback ($t(45)= -3.29$, $p= .002$, $d= -0.27$). No significant change across learning halves was observed for positive feedback ($p = .208$). In Learning Half 1, there was no significant difference between positive and negative feedback for older adults ($p =.395$), while this age group showed a larger FRN after positive than negative feedback in Learning Half 2 ($t(45)= 2.91$, $p= .006$, $d= 0.31$) (see Figure 4.5). In younger adults, FRN amplitudes differed significantly across learning halves following negative feedback, with larger amplitudes in Learning Half 2 than in Learning Half 1 ($t(51)= 2.65$, $p= .011$, $d= 0.44$). For positive feedback, the difference did not reach significance ($p= .078$). In addition, there was no significant difference

between negative and positive feedback in Learning Half 1 for younger adults (p= .415), but a larger FRN after negative as compared to positive feedback in Learning Half 2 (t(51) = -4.27, p<.001, d= -0.63) (see Figure 4.5).

Figure 4.5

Bar plot illustrating the interaction between Age, Valence and Learning Half

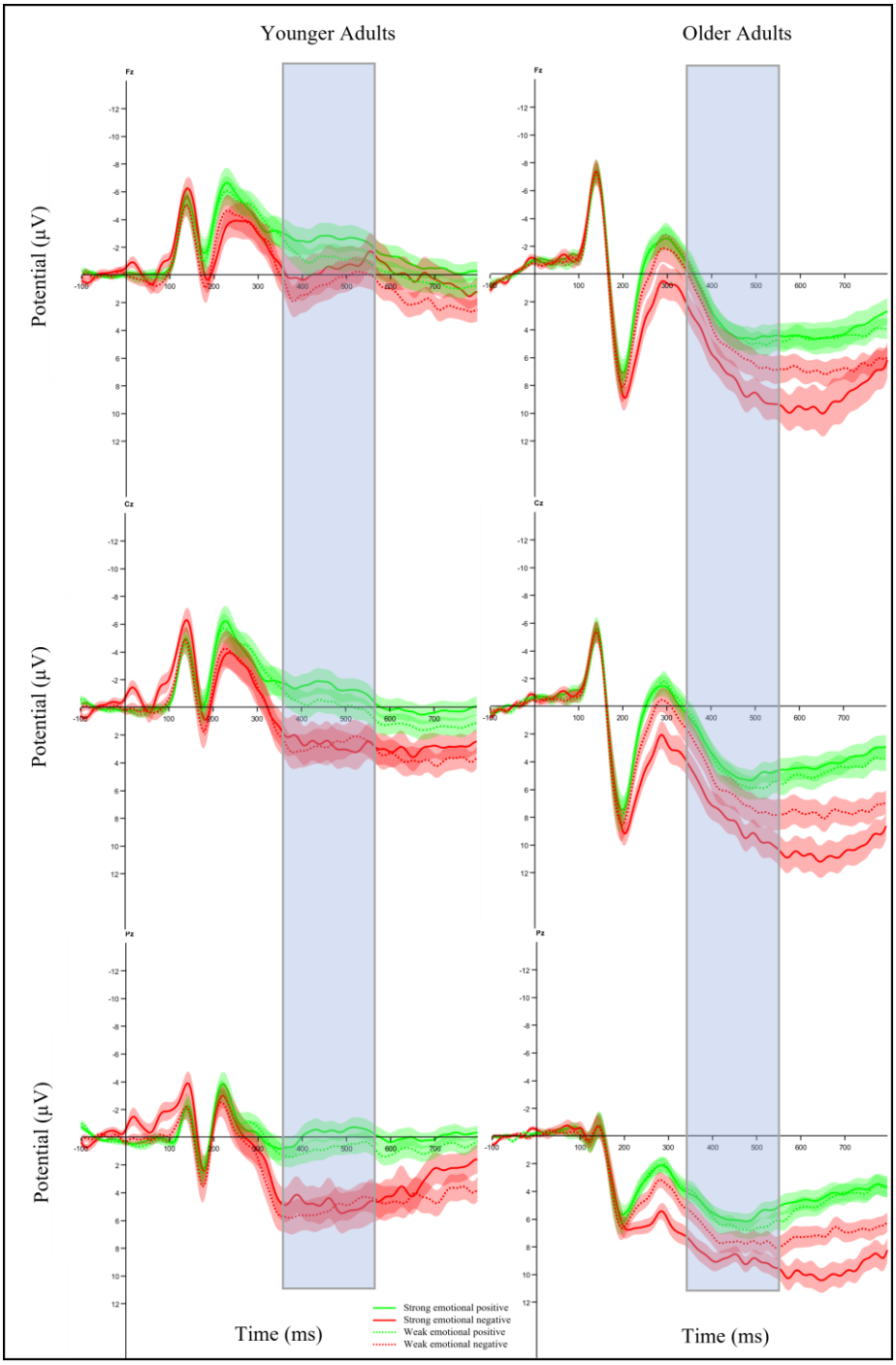


Note. Error bars represent the standard error of the mean.

4.4.2.2 P3b. The P3b ANOVA model (please see Figures 4.6 and 4.7) yielded a significant main effect of Age ($F(1,47)=18.98$, $p<.001$, $\eta_p^2= .29$), with older adults showing larger mean P3b amplitudes than younger adults. In addition, main effects for Valence ($F(1,47)=54.16$, $p<.001$, $\eta_p^2=.54$) and Channel ($F(2,94)=25.79$, $p<.001$, $\eta_p^2=.35$) were observed. Further, two-way interactions between Age and Feedback Condition ($F(1,47)=7.68$, $p=.008$, $\eta_p^2=.14$), Valence and Feedback Condition ($F(1,47)=9.79$, $p=.003$, $\eta_p^2=.17$), and Valence and Channel ($F(2,94)=11.94$, $p<.001$, $\eta_p^2=.20$) were found. Last, interactions between Age, Valence, and Channel ($F(2,94)=14.67$, $p<.001$, $\eta_p^2=.24$) and Age, Feedback Condition, and Channel ($F(2,94)=3.64$, $p=.030$, $\eta_p^2=.07$) were revealed.

Figure 4.6

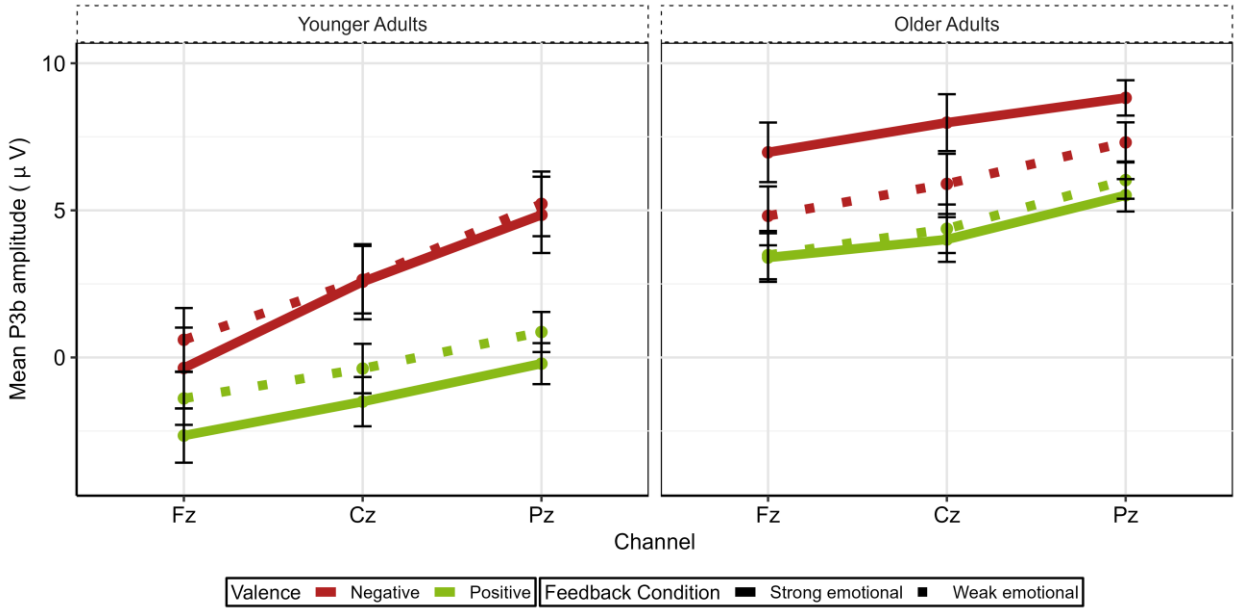
Feedback-locked ERP waveforms at three midline electrodes (Fz, Cz, Pz)



Note. Mean P3b time range is marked and shaded error bands represent the standard error of the mean.

Figure 4.7

Line plot illustrating the P3b topography



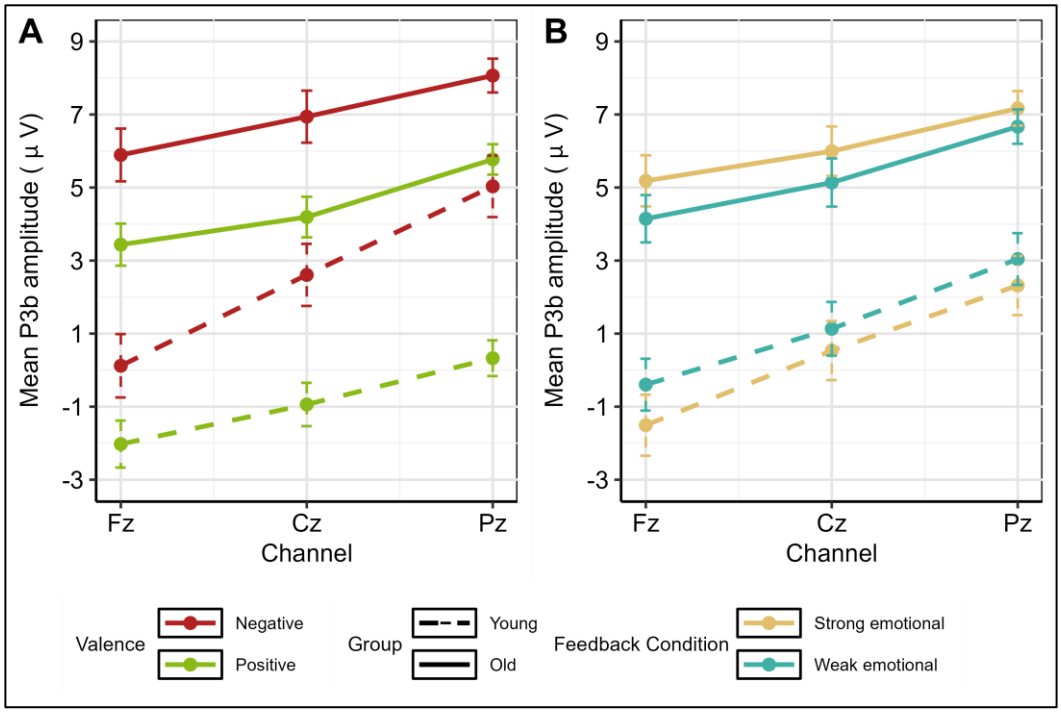
Note. Error bars represent the standard error of the mean.

To investigate age-related differences between groups, we next analyzed the two three-way interactions including the factor Age. For the interaction between Age, Valence, and Channel (please see Figure 4.8A), significant age-related differences were found at all three electrodes for negative and positive feedback, resulting in older adults having larger P3b amplitudes than younger adults (Fz: negative: $t(94.60)=5.11$, $p<.001$, $d=1.03$, positive: $t(95.80)=6.33$, $p<.001$, $d=1.27$; Cz: negative: $t(94.80)=3.91$, $p<.001$, $d=0.78$, positive: $t(96)=6.32$, $p<.001$, $d=1.27$; Pz: negative: $t(78.40)=3.16$, $p=.002$, $d=0.63$, positive: $t(95.10)=8.48$, $p<.001$, $d=1.70$). For the interaction between Age, Feedback Condition, and Channel, we found significant differences between younger and older adults in both feedback conditions at all three electrodes with older adults again showing larger P3b amplitudes (Strong emotional: Fz: $t(94.80)=6.15$, $p<.001$, $d=1.24$; Cz: $t(94.80)=5.18$, $p<.001$, $d=1.04$; Pz: $t(81)=5.17$, $p<.001$, $d=1.03$, Weak emotional: Fz: $t(95.90)=4.73$, $p<.001$,

d=0.95; Cz: *t*(95.80)=4.06, *p*<.001, *d*=0.82; Pz: *t*(86.70)=4.26, *p*<.001, *d*=0.85, please see Figure 4.8B).

Figure 4.8

Bar plot illustrating three-way interactions



Note. A) Interaction between Age, Valence and Channel and B) Age, Feedback Condition and Channel. Error bars represent the standard error of the mean.

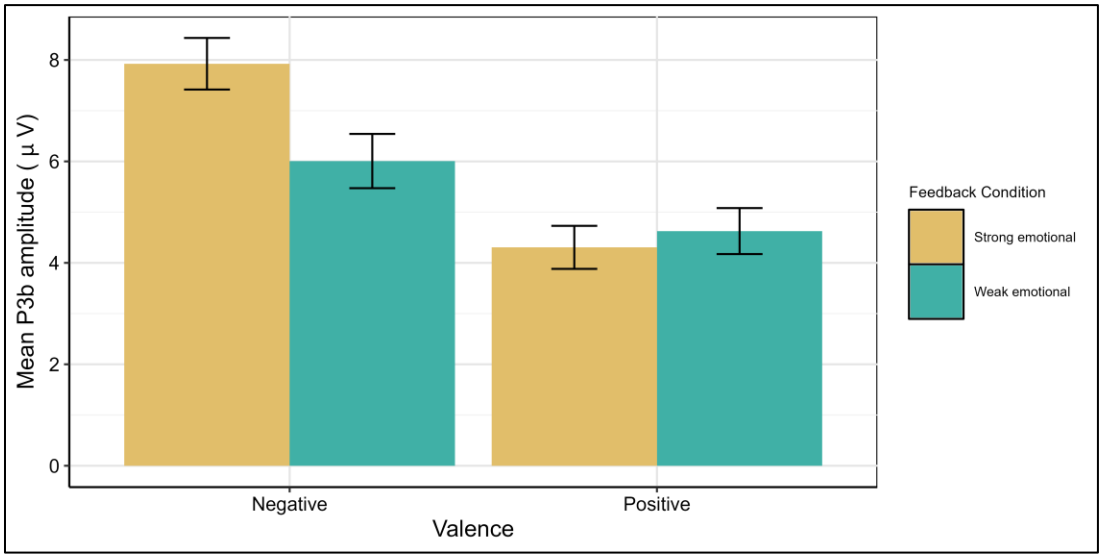
Next, guided by our hypotheses regarding age-specific effects, we conducted ANOVAs within age groups to examine the effects of valence and feedback condition. The analysis of younger adults resulted in significant main effects for Valence ($F(1,25)=29.64$, $p<.001$, $\eta_p^2=.54$) and Channel ($F(2,50)=17.29$, $p<.001$, $\eta_p^2=.41$), and an interaction between Valence and Channel ($F(2,50)=18.85$, $p<.001$, $\eta_p^2=.43$). For negative as well as positive feedback, the mean P3b showed a parietal focus as it was significantly larger at Pz vs. Cz (negative: $t(51)=-4.73$, $p<.001$, $d=-0.66$;

positive: $t(51)=–3.35$, $p=.002$, $d=–0.47$) and at Cz vs. Fz (negative: $t(51)=7.04$, $p<.001$, $d=0.98$; positive: $t(51)=4.18$, $p<.001$, $d=0.58$). In addition, P3b amplitudes were larger for negative relative to positive feedback at all electrode sites (Fz: $t(51)=3.96$, $p<.001$, $d=0.55$; Cz: $t(51)=6.61$, $p<.001$, $d=0.92$; Pz ($t(51)=8.37$, $p<.001$, $d=1.16$) with effect sizes increasing from frontal to parietal electrode sites (see Figure 4.8A).

The analysis of older adults revealed a significant main effect for Channel ($F(2,44)=9.14$, $p<.001$, $\eta_p^2=.30$), indicating a parietal distribution of the P3b for all conditions (Fz vs. Cz: $t(91)=5.26$, $p<.001$, $d=0.55$; Cz vs. Pz: $t(91)=-4.75$, $p<.001$, $d=0.49$). Moreover, a significant main effect for Valence ($F(1,22)=27.86$, $p<.001$, $\eta_p^2=.56$) and a significant interaction between Valence and Feedback Condition ($F(1,22)=12.25$, $p=.002$, $\eta_p^2=.36$) were revealed (please see Figure 4.9). After negative feedback, the mean P3b was larger after strong than weak emotional feedback ($t(68)=5.13$, $p<.001$, $d=0.62$), whereas after positive feedback, no such difference was found ($p=.202$). Additionally, in both feedback conditions, the mean P3b amplitude was larger after negative than positive feedback (strong emotional: $t(68)=10.2$, $p<.001$, $d=1.23$; weak emotional: $t(68)=4.19$, $p<.001$, $d=0.50$).

Figure 4.9

Interaction between Feedback Condition and Valence for older adults



Note. Whiskers denote standard error of the mean.

4.5 Discussion

In the present study, we investigated how different intensities of socio-emotional feedback influence learning in younger and older adults. We assumed that strong emotional feedback would support especially older adults to increase their learning performance. Furthermore, we examined whether strong emotional feedback would lead to an enhanced detection of unexpected outcomes, as reflected by the peak-to-peak FRN, and enhanced working memory updating, as indicated by the mean amplitude of the P3b. For this, participants performed a probabilistic learning task requiring them to learn stimulus–response associations, during which they received feedback through facial expressions conveying either weak or strong emotional feedback.

4.5.1 Learning Performance

The present findings provide evidence that learning from feedback is affected by both age and intensity of socio-emotional feedback. While younger participants outperformed older adults in terms of faster reaction times, accuracy was influenced by the type of feedback, which was presented. Learning performance improved over time in both age groups with reaction times decreasing steadily across the task, indicating general learning through feedback. While both groups' accuracy also improved, younger adults exhibited a steeper learning curve and reached peak performance earlier, whereas older adults showed slower and more gradual improvements, particularly during the earlier learning phases.

The type of feedback played a significant role in shaping learning performance. Across both age groups, strong emotional feedback led to higher accuracies and faster responses compared to weak emotional feedback. However, this benefit was particularly pronounced in older adults, as indicated by larger effect sizes for both accuracy and reaction times. The interaction between Age and Feedback Condition further supports the view that older adults profit disproportionately more from emotionally salient feedback (Ferdinand & Hilz, 2020). While both younger and older adults improved after strong emotional feedback, the gains were larger in the older group, suggesting that emotionally charged feedback may act as a motivational enhancer that reduces age-related learning deficits (Ferdinand & Hilz, 2020; Mather, 2012).

Notably, following strong emotional feedback, the performance of older adults reached the level of younger adults under the same condition. This finding is particularly noteworthy in light of well-documented age-related performance decline (Eppinger et al., 2008; Ferdinand, 2019; Lighthall et al., 2018; Mell et al., 2005; Pietschmann et al., 2011; Wild-Wall et al., 2009). Visual

inspection of the accuracy data further indicates that older adults in the strong emotional feedback condition performed comparably to younger adults in the weak emotional feedback condition. This pattern may reflect a motivationally driven benefit of emotional feedback by enhanced emotional engagement (Gorlick et al., 2013), enabling older adults to maintain cognitive control despite reduced learning rates.

At the same time, our findings add to prior evidence that younger adults can also benefit from socio-emotional feedback, for example in an item-category association task (Hurlemann et al., 2010) and probabilistic learning with varying task demands (Braunwarth & Ferdinand, 2025). However, in Ferdinand and Hilz (2020), younger adults did not show an accuracy benefit from socio-emotional compared to neutral feedback; their accuracy increased over the course of learning, but without significant differences between the feedback conditions. This observation suggests that the benefits of socio-emotional feedback in younger adults may have been masked by ceiling effects in that study.

Altogether, these findings highlight the role of emotional intensity in feedback learning and demonstrate that emotionally relevant feedback can facilitate performance across the lifespan. While potential ceiling effects in younger adults may have limited observable improvements, the overall pattern indicates benefits in both groups. In older adults in particular, preserved sensitivity to socio-emotional stimuli appears to enhance learning, underscoring the potential value of socio-emotional stimuli in targeted cognitive interventions.

4.5.2 Detection of unexpected events

In the present study, we expected the detection of unexpected events to be reduced in older adults compared to younger adults, but at the same time having significant differences in the

intensity of emotional feedback. Interestingly, older adults in our study exhibited larger peak-to-peak FRN amplitudes than younger adults. This finding deviates from previous studies reporting reduced performance monitoring and diminished FRN responses in older age, due to the age-related decline of dopaminergic signals (Bellebaum et al., 2011; Gajewski et al., 2018; Gajewski & Falkenstein, 2014; Hämmerer et al., 2011; Nieuwenhuis et al., 2005). However, our results are consistent with earlier work (Ferdinand & Hilz, 2020), in which older adults also showed enhanced detection of unexpected events following socio-emotional feedback (emotional vs. neutral faces), suggesting that socio-emotional feedback may preserve or even amplify the processing in older age. This could be grounded in motivational theories of aging, which imply that stimuli like faces, that can potentially convey socio-emotional information, might be valuable for shaping the motivation in performing a task successfully (Carstensen, 1991; Carstensen et al., 2006). However, this claim requires additional empirical support.

Unexpectedly, the effect of emotional intensity on the FRN was marginally non-significant. This is in contrast to a previous study, where socio-emotional feedback (emotional faces) led to a stronger processing of unexpected events in younger adults as compared to non-emotional feedback (scrambled faces; Braunwarth & Ferdinand, 2025). One possible explanation is that our study used faces with weak emotional expressions as the comparison condition, whereas the previous study employed scrambled faces, which differed more explicitly in emotional content. We used weak emotional expressions to create a comparison condition that matched the strong expressions on perceptual features while differing in intensity only. Nonetheless, despite the pronounced behavioral effects, the rapid detection mechanism reflected in the peak-to-peak FRN may not have been sufficiently sensitive to capture these more subtle variations in emotionality.

We also did not find a significant effect of feedback valence which is typically observed during feedback-induced learning when participants form outcome predictions (Holroyd & Coles, 2002; Martín, 2012; Paul et al., 2025). A reason for this could be that the valence effect changes with increasing learning.

Thus, we conducted post-hoc analyses taking learning progress into account. However, the trial numbers for negative feedback within the post-hoc analysis were low, therefore the results should be interpreted with caution. Nevertheless, these analyses showed that a valence differentiation arose with learning in younger adults, who exhibited a stronger FRN to negative feedback in the second half of the experiment. This is in line with the idea that negative feedback should become more unexpected the more participants have learned (Holroyd & Coles, 2002; Miltner et al., 1997). Older adults likewise showed no valence effect in the first half of learning. In the second half, however, they exhibited a more negative FRN to positive than to negative feedback, reflecting the opposite pattern of younger adults. One could speculate that this possibly indicates an age-related shift in the importance of positive feedback. Prioritizing positive information aligns with the well-documented positivity effect in aging (Mather & Carstensen, 2005; Reed et al., 2014) and has also been proposed in earlier studies on feedback-induced learning (Bellebaum et al., 2011; Eppinger et al., 2008). However, evidence for this effect remains inconsistent (Ferdinand, 2019; Ferdinand & Kray, 2013; Fernandes et al., 2018).

Taken together, our findings suggest that, compared with younger adults, older adults show enhanced detection of unexpected events when feedback is socio-emotional in nature, potentially reflecting age-related motivational shifts in feedback processing. While younger adults' monitoring system is especially sensitive for negative feedback once learning has been established, older adults show the opposite pattern, consistent with a positivity effect.

4.5.3 Working Memory Updating

The present findings revealed clear age-related differences in working memory updating, as indexed by the P3b. Interestingly, older adults showed larger P3b amplitudes than younger adults, suggesting enhanced updating mechanisms, which, however, has usually been found to be decreased with age in similar tasks (Ferdinand, 2019; Ferdinand & Kray, 2013; Schmitt et al., 2014a; West & Huet, 2020). One possible explanation for this could be that in our study, all of the feedback stimuli consisted of facial expressions, which due to their socio-emotional character may have a specific impact on the activation of working memory updating especially in older age. To our knowledge, the only other study examining feedback processing in the P3b in older and younger adults using emotional faces is the study by Ferdinand and Hilz (2020). In this study, however, age-differences in P3b amplitudes were not explicitly tested. Descriptively, however, P3b amplitudes for older adults do not seem to be enhanced in the emotional condition as compared to younger adults. Thus, it remains an open question for future research, which precise feedback stimulus characteristics can lead to larger P3b amplitudes in older adults.

In both younger and older adults, the P3b showed the expected parietal maximum, consistent with its role in updating working memory representations in response to task-relevant feedback (Gaál & Czigler, 2015; Martín, 2012; Polich, 2007).

In older adults, however, we assumed that the distribution over the scalp would be broader, with an enhanced frontal activation, likely reflecting the compensatory recruitment of additional resources to maintain effective updating when processing feedback (Cabeza et al., 2002; Daffner et al., 2011; Ferdinand, 2019; Ferdinand & Hilz, 2020; Friedman et al., 1997; Lubitz et al., 2017; Pietschmann et al., 2011; Reuter-Lorenz et al., 2000; Schmitt et al., 2014a, 2014b; Tregellas et al.,

2006; Wild-Wall et al., 2009). One possible explanation is that the feedback stimuli were clearly interpretable, given that both feedback conditions used similar facial expressions differing only in emotional intensity and that the task itself was comparatively easy. Nevertheless, a possible replication of these findings is an open topic for future research.

Across both age groups, working memory updating was larger for negative than positive feedback. This indicates that negative feedback elicited a stronger updating of task-relevant representations, consistent with the requirement to adapt behavior after errors in probabilistic learning tasks (Braunwarth & Ferdinand, 2025; Ferdinand, 2019; Ferdinand & Hilz, 2020; Frank et al., 2005; Kamp et al., 2024). Among younger adults, we observed a clear valence effect that was not modulated by emotional intensity. This finding indicates that efficient updating processes in this age group operate independently of the emotional intensity of feedback. It also replicates the results of Ferdinand and Hilz (2020), who found that socio-emotional feedback per se did not enhance working memory updating in younger adults, but negative feedback did.

In the present study, we found no main effects or interactions involving emotional intensity in younger adults. However, this is in contrast to Braunwarth and Ferdinand (2025), who did report effects of emotionality for younger adults. One possible explanation is that in the present study both feedback conditions were socio-emotional in nature, as they both contained faces with weak and strong emotional expressions, whereas in Braunwarth and Ferdinand (2025) one condition consisted of scrambled faces and thus most likely lost most of their socio-emotional aspects. Therefore, the latter study provided a more explicit contrast, potentially increasing the relevance of socio-emotional feedback in working memory updating.

In contrast, and most notably, older adults exhibited a marked effect of emotional intensity in the age-specific analyses: Working memory updating following negative feedback was significantly larger for strong than for weak emotional feedback. This finding replicates the results of Ferdinand and Hilz (2020), and supports the notion that socio-emotional feedback benefits older adults' working memory updating. However, an alternative explanation could be that older adults may have greater difficulty differentiating feedback valence when emotional intensity is weak, possibly due to subtle changes in emotion perception with age (Ruffman et al., 2008). However, this interpretation is challenged by the fact that learning performance after weak emotional feedback was comparable to earlier studies such as the neutral and socio-emotional feedback conditions in Ferdinand and Hilz (2020) (both below and around 0.7 relative frequency of correct responses in last learning block) and that performance after strong emotional feedback was exceptionally high. This high performance may also be related to the choice of happiness and disgust as feedback emotions, since recognition of these expressions is usually well maintained in older adults (Orgeta & Phillips, 2007; Ruffman et al., 2008). Therefore, we assume that strong emotional feedback can substantially enhance working memory updating in older adults by activating the dopaminergic system, compensating for age-related impairments (Bäckman et al., 2000; Bäckman et al., 2006).

4.5.4 Limitations and Outlook

One possible limitation of the present study could be that the age of participants who rated the emotional intensity and valence of feedback in the preliminary study was significantly younger (mean age= 24.39, range= 18–56 years) than those included in the older age group of the present study. This may have resulted in older adults recognizing the feedback stimuli less well than younger adults. Consequently, the stimuli may not have been equally valid for different age groups,

which could lead to an overestimation of socio-emotional feedback processing and how effectively older adults can learn from it. However, one could argue that such discrepancies are meaningful in themselves, since older adults are likely to have different thresholds for interpreting emotional signals. Furthermore, learning performance in the weak emotional condition was consistent with earlier studies. In the strong emotional condition, however, we observed a steep increase, possibly due to the use of happy and disgusted facial expressions. Nevertheless, future research should aim to validate feedback stimuli for different age groups. Potential ceiling effects in younger adults may have limited observable improvements in the benefit of socio-emotional feedback during learning as well. Moreover, we cannot determine whether the socio-emotional benefit observed in this study is driven by the emotional expression of the faces, the social nature of the faces themselves, or the inherent communicative meaning of emotional expressions. Therefore, future research could benefit from developing feedback stimuli that can distinguish between these different options. This would not only increase methodological precision, but also provide deeper insights into how socio-emotional feedback is used by older adults during learning.

4.5.5 Conclusion

In this study, we found that both groups learning performance benefited from strong emotional feedback, while the effect was particularly pronounced for older adults. Interestingly, older adults showed a generally stronger detection of unexpected events, as reflected in the FRN, which we assume might be due to the socio-emotional content of the feedback stimuli we used. Our findings further suggest that strong socio-emotional feedback strengthens working memory updating in older adults and, under optimal conditions, may enable older adults to reach performance levels comparable to those of younger adults. This has important implications for developing targeted cognitive training programs, refining feedback strategies, and designing

evidence-based interventions that strengthen learning in older adults, thereby promoting autonomy and sustained engagement in everyday life.

5 Study 3: Electrophysiological correlates of learning from social feedback in younger and older adults

Authors: Braunwarth, Jana Isabelle[1]; Lorenz, Corinna[1]; Pfabigan, Daniela Melitta[2]; Ferdinand, Nicola Kristina[1]

Affiliations: [1]Department of Psychology, University of Wuppertal, Germany, [2]Department for Medical and Biological Psychology, University of Bergen, Norway

Status: In preparation for submission.

Acknowledgment: We gratefully acknowledge all participants for their time and commitment to this study. This study is part of JIB´s dissertation project.

Conflict of Interest: We declare no conflict of interest.

Author´s contributions: JIB: Conceptualization, Data Curation, Formal Analysis, Methodology, Writing - Original Draft Preparation, Project administration, Software, Validation, Visualization, Writing - Review & Editing; **CL**: Project administration, Conceptualization, Writing - Review & Editing; **DMP**: Conceptualization, Resources, Writing - Review & Editing;**NKF**: Conceptualization, Funding Acquisition, Investigation, Resources, Supervision, Validation, Writing - Review & Editing.

Published Preprint: https://doi.org/10.31234/osf.io/9pgqy_v1

Keywords: Feedback Processing, Feedback-Related Negativity (FRN), P3b, Social Feedback, Aging

5.1 Abstract

Feedback learning supports flexible behavior in changing environmental contexts, but declines with age. Motivational aging theories, however, suggest that socio-emotional feedback can reduce these deficits, though it is unclear whether this effect depends on the social, emotional or communicative information in feedback. Participants from two age groups, *n*= 24 older adults (*M* = 72.37 years; *SD*=3.37) and *n* = 22 younger adults (*M* = 22.63 years; *SD*=1.78), therefore completed a probabilistic learning task in which stimulus–response associations had to be learned via unfamiliar social (hand gestures) or non-social (abstract shapes) feedback. To capture neural correlates of feedback processing, two ERP components were investigated; the feedback-related negativity (FRN), associated with the detection of unexpected events, and the P3b component, linked to working memory updating. Results revealed that younger and older adults learned more effectively from social than non-social feedback, with older adults benefitting most. The FRN was enhanced after social feedback in older adults, but after non-social feedback in younger adults. The P3b was more pronounced for social feedback, primarily driven by larger valence-related differences. In contrast, non-social feedback elicited increased frontal activation, indicating higher processing effort irrespective of participants' age. These findings reveal a processing advantage for social feedback that appears biologically rooted rather than primarily explained by motivational aging theories, which may require additional facets such as emotional or communicative information.

5.2 Introduction

Adapting behavior through feedback is a fundamental learning strategy throughout the life span. As populations age, it becomes increasingly important to understand how these processes change with age, how they manifest neurally, and whether specific measures can counteract

potential deficits. Recent research shows that age-related impairments in feedback processing and learning may be reduced through socio-emotional feedback, in the form of facial feedback (Ferdinand & Hilz, 2020; Gorlick et al., 2013). Nevertheless, prior studies often use stimuli that combine multiple features, emotional, social, and communicative information, making it unclear which facet drives the observed advantages of socio-emotional feedback, particularly in older adults. To address this gap, the present study manipulated the social content of feedback while minimizing its emotional and communicative components in a probabilistic learning task.

5.2.1 Learning from feedback

Learning is a fundamental process that enables us to adapt our behavior in different contexts. Feedback and the possible discrepancies between expected and actual outcomes are encoded by the brain as prediction errors, which update internal representations to change our future decisions (Schultz, 2002). Midbrain dopaminergic neurons, particularly within the ventral striatum, have been shown to signal these prediction errors and relay them to frontal areas. Within the corticostriatal circuitry, the basal ganglia contribute to action selection during reinforcement, while the dorsal anterior cingulate cortex (dACC) integrates feedback information to adjust cognitive control and guides flexible behavior, possibly resulting in adaptation (Alexander & Brown, 2011; Braver et al., 2001; Cohen, 2008; Haber, 2016; Holroyd & Coles, 2002; Schultz, 2002).

This can be examined using event-related potentials (ERPs). The Feedback-Related Negativity (FRN) is a negative waveform, mostly pronounced over fronto-central areas around 200-300ms post feedback (Miltner et al., 1997). It is assumed to be functionally related to the detection of unexpected events and thereby measuring a person´s expectancy violation (Ferdinand et al., 2012; Paul et al., 2025; Pfabigan et al., 2011; Talmi et al., 2013), representing an unsigned

prediction error. On the other hand, research showed that the FRN is often larger after negative than positive feedback, or "worse than expected" outcomes, representing a signed prediction error (Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Sambrook & Goslin, 2014). An alternative account even emphasizes the Reward Positivity (RewP), a positive deflection at the same time window, which rather reflects a reward sensitive (or "better than expected") signal (Holroyd et al., 2008b; Krigolson, 2018; Proudfit, 2015). Because the FRN better reflects expectancy violations than the RewP, and these violations are key to probabilistic learning, we focus on the FRN.

A second important ERP during learning from feedback is the P3b component, a positive going waveform most pronounced at parieto-central areas at around 300-500ms post feedback, representing the updating of working memory by integrating relevant information (Bellebaum & Daum, 2008; Donchin & Coles, 1988; Martín, 2012; Polich, 2007; Severo et al., 2020; Ullsperger et al., 2014; Walentowska et al., 2016). It has been shown to be more sensitive to task-relevant valence (Mecklinger et al., 1994), e.g., which feedback is considered to be more relevant to perform a task successfully (Frank et al., 2005), and can be modulated by expectancy and informational value of the feedback during learning (Borries et al., 2013; Ferdinand, 2019; Ferdinand & Kray, 2013; Fischer & Ullsperger, 2013).

5.2.2 Age-related alterations in learning from feedback

Healthy aging is characterized by neurobiological alterations, including declines in dopaminergic transmission which involves reduced firing efficiency and receptor density (Bäckman et al., 2000; Bäckman et al., 2006; Lighthall et al., 2018). Such age-related changes have been observed in reduced working memory, slower processing speed, and less flexible behavior (Eppinger et al., 2011; Hedden & Gabrieli, 2004; Park et al., 2001; Verhaeghen & Salthouse, 1997).

Learning tasks revealed that older adults learn slower and commit more errors than younger adults (Ferdinand, 2019; Ferdinand & Hilz, 2020; Mell et al., 2005; Wild-Wall et al., 2009). These changes in behavioral learning performance have also been investigated on an electrophysiological level, showing reduced detection of unexpected events, reflected in a less distinct valence effect for the FRN component, and less effective working memory updating as measured by reduced P3b amplitudes (Eppinger et al., 2008; Ferdinand, 2019; Hämmerer et al., 2011; Herbert et al., 2011; Pietschmann et al., 2008, 2011; West & Huet, 2020). Modulations of P3b amplitudes are additionally paralleled by a more widespread distribution extending into fronto-central regions, possibly reflecting compensatory recruitment of frontal networks to maintain performance (Cabeza et al., 2002; Ferdinand, 2019; Friedman et al., 1997, 2007; Lubitz et al., 2017; Pietschmann et al., 2011; Reuter-Lorenz et al., 2000; West & Huet, 2020).

5.2.3 Socio-emotional feedback and aging

Most research indicates that older adults show reduced feedback processing during learning, as reflected in ERPs (Eppinger et al., 2008; Ferdinand, 2019, 2019; Ferdinand & Hilz, 2020; Hämmerer et al., 2011; Herbert et al., 2011; Mell et al., 2005; Pietschmann et al., 2008, 2011; West & Huet, 2020; Wild-Wall et al., 2009). However, this does not imply that feedback loses relevance with age. Motivational aging theories propose that priorities shift toward emotionally meaningful and socially rewarding information across the lifespan (Carstensen, 1991; Carstensen et al., 2006; Charles, 2010; Charles & Luong, 2013; Charles & Piazza, 2024). Thus, feedback relevance may depend on feedback type rather than diminishing in general. Although these theories suggest that older adults could benefit from social or emotional feedback, empirical evidence remains scarce.

Research suggests that socio-emotional feedback (in particular faces used as feedback stimuli) enhances learning performance in older adults, a benefit that is usually not observed in younger participants (Ferdinand & Hilz, 2020; Gorlick et al., 2013; Legaz et al., 2022). The beneficial effects of socio-emotional feedback were also evident in the accuracy among older adults in a study by Ferdinand and Hilz (2020), which involved a probabilistic learning task. The authors also used ERPs to examine learning and feedback processing. At the neurophysiological level, the findings were consistent with the behavioral data. In the later P3b stage, older adults used the type of feedback to update working memory, showing larger P3b responses to negative and socio-emotional feedback. Younger adults, in contrast, relied only on feedback valence, not type. In the early phase of feedback processing, older adults exhibited a larger FRN component, especially in response to neutral faces, implying that neutral expressions may carry emotional negative information (Ferdinand & Hilz, 2020; Lee et al., 2008).

Building on this, a follow-up study replaced socio-emotional (emotional face) vs. non-emotional (neutral face) feedback with faces displaying weak vs. strong emotional expressions to examine learning benefits and feedback-locked ERPs in older adults (Braunwarth & Ferdinand, 2025b). This study found that strong emotional feedback was associated with markedly improved learning in older adults as their learning accuracy almost reached the accuracy level of younger adults after weak emotional feedback. In detecting unexpected events, older adults again showed larger FRN amplitudes than younger adults for both weak and strong feedback, suggesting that socio-emotional feedback in particular may give older adults a processing advantage. Working memory updating was especially enhanced after strong emotional negative feedback, whereas no differences between strong or weak emotional feedback were found after positive feedback. Results in younger adults are less consistent in learning from socio-emotional feedback, ranging from no

processing benefits (no difference in FRN and P3b after socio-emotional vs. non-emotional feedback) (Ferdinand & Hilz, 2020), to better learning and processing benefits after socio-emotional feedback (Braunwarth & Ferdinand, 2025; Hurlemann et al., 2010; Schulreich et al., 2013).

Yet, all of the presented studies rely on facial feedback to investigate age-related benefits in learning. ERP studies investigating the processing of social feedback without emotional information, as it is present in facial expressions, revealed again an advantage of social (thumbs up vs. thumbs down) compared to non-social feedback (abstract forms) in younger adults. This advantage was reflected in enhanced FRN and P3b amplitudes in time estimation tasks (Pfabigan et al., 2019; Pfabigan & Han, 2019). Based on this, one could assume that social stimuli, which are used as a communication signal lead to a processing advantage also in younger adults.

Nevertheless, the findings underscore the difficulty of disentangling the partly overlapping facets of socio-emotional feedback: Sociality, emotionality, and communicative meaning, and their contributions to learning. Social feedback can be provided in many ways, such as through body language, voices, the simple presence of others, or their evaluations. Social feedback can also carry culturally learned communicative meanings such as geometric shapes (check mark vs. x) or gestures (thumbs up/down) (Dekkers et al., 2015; Koban et al., 2012; Molen et al., 2017; Peters et al., 2024; Pfabigan et al., 2018; Voegler et al., 2019). The importance of learned communicative meaning is comparable to entering a café in search of a seat: someone notices you entering and shifts their bag; social feedback without a fixed meaning. But if they add a clear, culturally learned gesture, like a nod or inviting wave, it becomes social feedback with communicative meaning: a shared signal that you may sit down. In contrast, emotional feedback conveys internal affective states (satisfaction, frustration) through facial or non-facial modalities such as tone of voice,

musical elements, or abstract stimuli with inherent emotional qualities (e.g., warm vs. cold colors, aversive pictures, emojis) (Olofsson et al., 2008; Weiß et al., 2019). Socio-emotional faces, finally, combine all facets, as they simultaneously convey social information, emotions, as well as a communicative meaning. This differentiation is further complicated by the common practice of broadly labeling such stimuli as social or emotional feedback (Braunwarth & Ferdinand, 2025; Coles et al., 2019; Ferdinand & Hilz, 2020; Weiß et al., 2020), overlooking finer distinctions. Although this mirrors real-world conditions in which these facets rarely occur in isolation, the present study intentionally manipulated the content of socio-emotional feedback to focus on how basic social information, without emotional or communicative meaning, contribute to learning benefits in older adults.

5.2.4 The present study

In the present study, we therefore aimed to disentangle the different facets (social, emotional, communicative meaning) inherent to socio-emotional feedback. Thus, we manipulated the sociality of the feedback stimuli while concurrently minimizing emotional and communicative information in these stimuli. To address this, the study employed pre-rated unfamiliar social stimuli (unknown hand gestures) and non-social stimuli (abstract shapes) as feedback.

We predicted that both younger and older adults would benefit more from social than from non-social feedback, reflected in stronger increases in accuracy and faster reaction times over the course of the learning task. On the neural level, we expected both groups to exhibit enhanced early feedback processing for social stimuli, expressed as a larger peak-to-peak FRN component. Additionally, we hypothesized that older adults would show an even larger FRN difference between social and non-social feedback compared to younger adults, pointing to a heightened

motivational sensitivity to sociality. With regard to later processing stages, we anticipated that both age groups would demonstrate stronger working memory updating following social relative to non-social feedback, indexed by a larger mean P3b component. Finally, we expected older adults, to display a heightened mean P3b after receiving social feedback with a more anterior distribution compared to non-social feedback, suggesting compensatory mechanisms during working memory updating relative to younger adults.

5.3 Methods

This study was preregistered on the Open Science Framework, including specifications of sample size, variables, hypotheses, and planned analyses (https://osf.io/xb5j3/). Any deviations from the preregistration will be clearly indicated.

5.3.1 Participants

To determine the required sample size for the study, we conducted an a priori power analysis using G*Power software (Faul et al., 2007), guided by effect size estimates reported in previous literature (Braunwarth & Ferdinand, 2025; Ferdinand & Hilz, 2020). The parameters included an expected effect size of $f = 0.15$ (small to medium range), a desired statistical power of 0.80, and an α-level set at 0.05. The analysis indicated that at least 18 participants per group would be necessary to detect the most complex anticipated interaction (P3b: 2x2x3). To compensate for dropouts, we recruited a minimum of 25 individuals in each age group: younger adults aged 19–29 years and older adults aged 67–80 years. However, we realized that this was not the most adequate way to estimate sample size, so we performed another analysis, which was not preregistered, using PANGEA (Westfall, 2016) that confirmed the above estimation results. With a $d = 0.40$ and $n = 25$ per group for the Valence x Feedback Condition x Channel interaction, the calculated power was

81.5%. Recruitment strategies involved adverts in social media and the University of Wuppertal's SONA participant recruitment system. For older adults, we additionally distributed flyers at community centers, sports associations, and cultural institutions. Participants received either course credit or a financial compensation of €10 per hour. Eligibility criteria included right-handedness, no history of neurological or psychiatric illness, no colorblindness, no implanted medical devices (e.g., pacemakers, cochlear implants), and normal or corrected-to-normal vision. Cognitive status was evaluated via the MMSE, with a cutoff of >27 ensuring cognitive integrity (Folstein et al., 1975; Salis et al., 2023). We followed the Declaration of Helsinki and the study was approved by the ethics committee of the University of Wuppertal. All participants signed informed consent before participation. Six participants (three younger, three older adults) were excluded from analyses: four for excessive EEG artifacts (>25% of trials), one older adult for insufficient task comprehension, and one for current psychotropic medication use. Thus, in total, n= 22 younger and n= 24 older adults were included in the analyses. Participants were also tested on the Digit Symbol Substitution Test (DSST; adapted from Wechsler; Jaeger, 2018) and the Multiple-Choice Knowledge Test (MWT-B; adapted from Lehrl, 2005) to assess fluid and crystallized intelligence. As expected, younger adults' performance was better compared to older adults in the DSST (t(44) = -7.44, p <.001, d= 2.31, two-tailed), while older adults outperformed younger adults in the MWT-B (t(44) = 7.81; p <.001, d= -2.20, two-tailed). Demographic details of the final sample can be found in table 1.

Table 5.1

Group Demographics

	Older adults	Younger adults
Mean Age in years (SD)	72.4 (3.4)	22.6 (1.8)
Number of participants (men/women/divers)	16/8/0	13/8/1
Mean correct MWT responses (SD)	27.1 (2.7)	20.5 (2.6)
Mean correct DSST responses (SD)	44 (9.8)	62.4 (6.9)

Note. MWT = Multiple Choice Vocabulary Test, DSST = Digit Symbol Substitution Test.

5.3.2 Probabilistic Learning Task

The participants completed a probabilistic learning task in the present study, in which they were asked to link objects to one of two keys by pressing either the black ("c") or the white ("m") colored button on a standard QUERZ keyboard, followed by feedback (for similar paradigm see (Braunwarth & Ferdinand, 2025; Ferdinand & Hilz, 2020)). The object pictures (object categories like fruits, animals, furniture) were taken from a standardized database and presented with a pixel size of 281x197 or 197x281 (Rossion & Pourtois, 2004). Each object was either linked to social or non-social feedback. Participants were told a cover story in which they acted as movers loading objects into either a black or white truck. After each decision, they received feedback from their boss, which was, however, invalid on 10% of trials because the boss had not observed the loading correctly. The participants were additionally told that these cases were rarely and they should not be irritated by them. The experimental procedure comprised a total of 720 trials, organized into

four learning blocks of 180 trials each. Within each block, participants were required to assign six objects to the trucks. Prior to the main task, participants completed eight practice trials, which could be repeated upon request. Short breaks were provided after every 60 trials, with participants allowed to determine the length of the break. Following each learning block, a brief retrieval task was administered in which all previously encountered objects were presented again. In order to account for individual and age-related differences in processing speed, response time was adaptively adjusted throughout the task (Eppinger et al., 2008; Ferdinand & Hilz, 2020). Each trial began with a fixation cross presented for 500 ms, followed by the object. The initial response time was set at 1000 ms. If this window was exceeded, participants received on-screen feedback indicating "zu langsam" (German for "too slow"). If participants consistently responded within the allowed time across 20 consecutive trials, the response window was shortened by 100 ms for the following 20 trials. If the window was exceeded once, it remained unchanged; if exceeded more than once, the time limit was increased by 100 ms. This adaptive mechanism operated within a range of 600 to 1500 ms. After the response was given, a blank screen appeared for 500 ms, followed by either social or non-social feedback displayed for 700 ms. An inter-trial interval of 300 ms concluded each trial (see Figure 5.1).

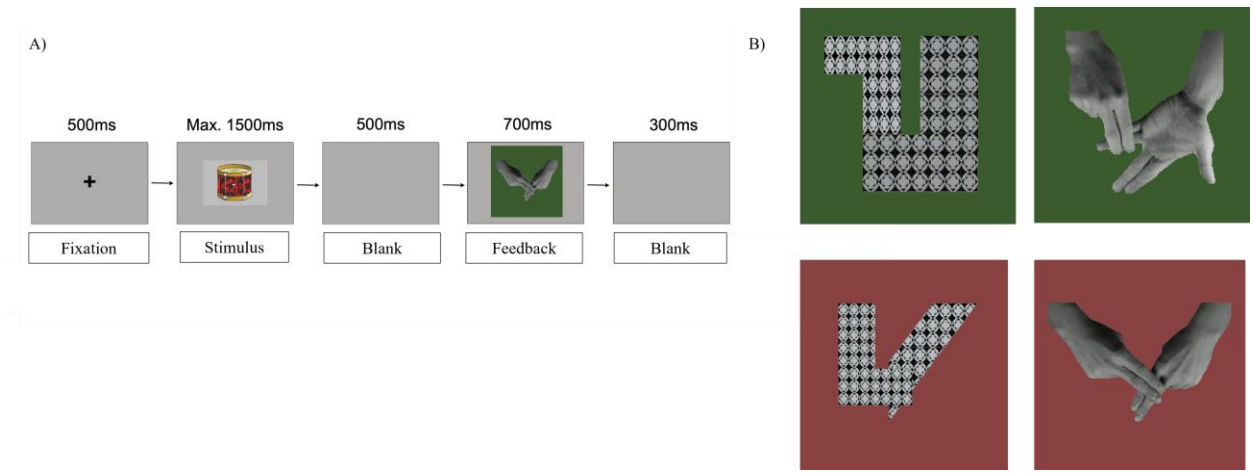
5.3.3 Feedback Stimuli

Social feedback stimuli were custom-developed from simplified British Sign Language hand gestures, with matching non-social abstract shapes approximating their contours, all presented at a resolution of 200×200 pixels and created in Adobe Photoshop (Adobe Systems, San Jose, CA). To ensure comparability between stimulus types, an online pre-study was conducted in which N = 70 participants (M = 33.5 years, SD = 10.1, range: 18–66) rated six pairs of social and non-social images on stimulus complexity, valence, familiarity, and arousal using 7-point Likert scales. The

goal was to identify unfamiliar yet matched pairs across conditions. Statistical comparisons using Kruskal–Wallis tests (for detailed analyses, please see supplementary material) guided the selection of stimulus pairs for the main experiment (see Figure 5.1). To clearly indicate the valence of feedback while keeping the stimulus content social or non-social, background color was used: green signaled positive feedback, and red indicated negative feedback (all stimuli matched for visual luminance). To control for potential bias in stimulus presentation, the assignment of valence was counterbalanced across participants. Specifically, stimulus pair 4 was presented with positive valence for one subgroup and negative valence for the other, while the valence assignment for pair 6 was reversed accordingly. This procedure ensured an even distribution of valence combinations within the sample.

Figure 5.1

Exemplary trial and illustration of feedback stimuli



Note. A) Exemplary trial and B) illustration of positive feedback (green) and B) negative (red) feedback for social (right) and non-social (left) condition.

5.3.4 Procedure

Upon arrival, participants provided informed consent. Older adults completed the Mini-Mental State Examination (MMSE; Folstein et al. (1975)) to screen for cognitive decline. Handedness was assessed in both age groups using the Edinburgh Handedness Inventory (LQ; Oldfield (1971)). Subsequently, all participants completed the Digit Symbol Substitution Test (DSST; Jaeger, 2018) as a measure of fluid intelligence, along with a demographic questionnaire. Additional self-report measures included an assessment of social network size (Fu, 2005), an adapted version of the Social Participation Questionnaire (Densley et al., 2013), and questionnaires assessing emotion regulation and empathy, including the German versions of the Emotion Regulation Questionnaire (ERQ; Abler and Kessler, 2011) and the Interpersonal Reactivity Index (IRI; Paulus, 2009). Participants also rated their perceived intimacy with their three closest social contacts and indicated the nature of each relationship. These measures will be reported in detail elsewhere. Crystallized intelligence was assessed using the digital version of the Multiple-Choice Vocabulary Test (MWT-B; Lehrl, 2005). Afterwards, participants were prepared for EEG recording. The probabilistic learning task was administered on a 27-inch DELL UP2716D monitor in an electrically shielded, sound-attenuated EEG cabin. After completion, participants answered follow-up questions regarding sleep, concentration, hunger, and learning strategies. Finally, they received compensation and were debriefed before departing.

5.3.5 EEG Recording and Analysis

EEG data were acquired using BrainVision Recorder (Version 1.23.0003, Brain Products GmbH, Gilching, Germany), with the BrainVision Brain AmpDC amplifier, while the experimental task was presented with E-Prime 3.0 (Psychology Software Tools, Pittsburgh, PA, USA). A total of 58 active Ag/AgCl electrodes were positioned according to the international 10–20 system

(Jasper, 1958). The ground electrode was placed at AFz, and the left mastoid served as online reference. To monitor eye movements and blinks, vertical and horizontal electrooculogram (EOG) was recorded using electrodes positioned above and below the right eye and near the outer canthi of both eyes. All electrode impedances were kept below 20 kΩ. EEG and EOG signals were digitized at a sampling rate of 500Hz and filtered online with a low-pass filter at 250 Hz.

Offline preprocessing was conducted in MATLAB R2023 (Inc., 2022) using EEGLAB v2021.1 (Delorme & Makeig, 2004). Data were band-pass filtered using a linear non-casual FIR filter with a high-pass filter at 0.01 Hz (transition band width: 0.01Hz, passband edge: 0.01Hz, cutoff frequency (-6dB): 0.005 Hz) and a low-pass filter at 30 Hz (transition band width: 7.5Hz, passband edge: 30Hz, cutoff frequency (-6dB): 33.75 Hz). The data were additionally downsampled to 250 Hz. Afterwards, EEG data were re-referenced to linked mastoids. Independent component analysis (ICA) was applied to identify and remove artifacts, particularly those related to eye movements and blinks. Components were classified and rejected semi-automatically using ICLabel (Pion-Tonachini et al., 2019) and visual inspection. Following artifact correction, epochs of 900ms with a pre-stimulus baseline of -100 (-100 ms to 800 ms) were extracted for the relevant segments (social positive, non-social positive, social negative, non-social negative) with ERPLAB v8.30 (Lopez-Calderon & Luck, 2014). In a last step, trials exceeding ±75µV were semi-automatically excluded from further analysis. Thus, the mean number of included trials was 241.37 (*SD* = 33.86) for social positive, 67.13 (*SD* = 30.43) for social negative, 224.15 (*SD* = 33.80) for non-social positive, and 80.54 (*SD* = 31.39) for non-social negative feedback trials.

The feedback-related negativity (FRN) was quantified at electrode FCz as the peak-to-peak difference between the positive deflection (180–240 ms) and the subsequent negative deflection (240–340 ms) following feedback in older adults (Ferdinand, 2019; Ferdinand & Hilz, 2020;

Holroyd & Coles, 2002). For younger participants, visual inspection suggested that this interval was not optimal, because the preregistered time window did not capture the respective peaks. Therefore, we determined the FRN as the positive peak within 170–230 ms and the negative peak within 230–330 ms (Luck & Gaspelin, 2017), which resulted in a deviation from our preregistered plan.

A comparable adjustment was necessary for the mean P3b. This component was first identified based on the grand-average peak within a 300–600 ms post-feedback window. Subsequently, a window of ±75ms was centered on the respective group peak and used to compute the mean amplitude (Martín, 2012; Polich, 2007). For older adults, this resulted in a measurement window of 425–575 ms, whereas for younger adults the corresponding interval was 295–445 ms. Finally, to assess potential age-related anterior shifts in P3b topography, analyses were conducted across three midline electrodes (Fz, Cz, and Pz).

5.3.6 Data analysis

To assess accuracy and reaction times, we performed mixed ANOVAs with Group (Young, Old) as between-subject factor and Feedback Condition (Social, Non-social) and Learning Quarter (LQ) (1,2,3,4) as within-subject factors. Trials with reaction times < 100ms were excluded from behavioral analyses. For the analysis of the reaction times, we used correct trials only. To reduce the number of comparisons, in case of significant effects or interactions with learning quarter, pairwise comparisons between LQ1 vs. LQ2, LQ2 vs. LQ3 and LQ3 vs. LQ4 were calculated.

FRN (peak-to-peak) amplitudes were analyzed using a mixed-design ANOVA with Group (Young, Old) as a between-subject factor, and Feedback Condition (Social, Non-social) and Feedback Valence (Positive, Negative) as within-subject factors at channel FCz. Mean P3b

amplitudes were examined using a mixed-design ANOVA with Group as a between-subject factor, and Feedback Condition, Feedback Valence, and Channel (Fz, Cz, Pz) as within-subject factors. Planned contrasts between Fz vs. Cz and Cz vs. Pz were included to assess topographical differences across age groups.

If necessary, Greenhouse-Geisser correction was applied for sphericity violations. In this scenario, both epsilon-corrected p-values and their corresponding uncorrected degrees of freedom are provided. Additionally, we will report Cohen´s d effect sizes for pairwise comparisons (Cohen, 1988). Bonferroni correction was applied for post-hoc testing. Significance level was set to $\alpha = .05$ for all analyses, which we computed in RStudio Version 4.3.2. (R Core Team, 2023).

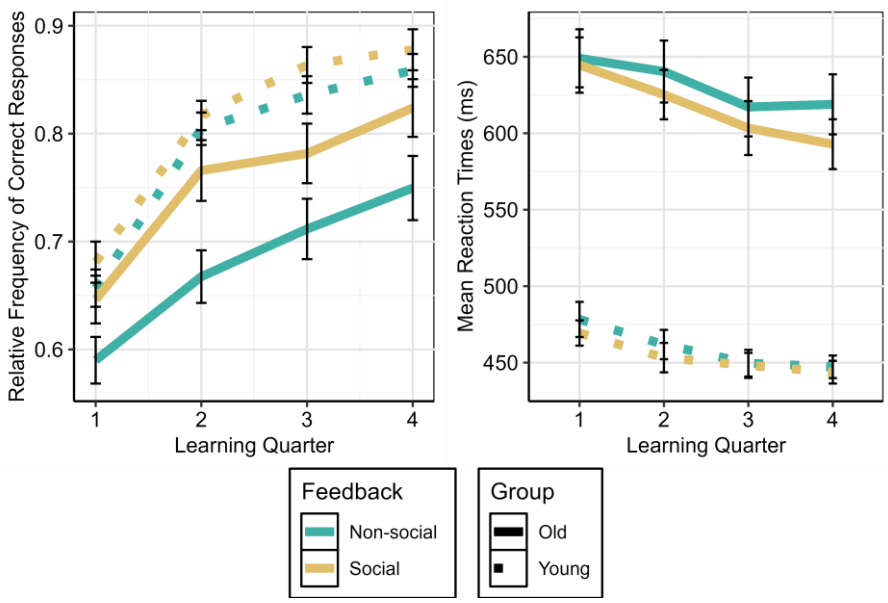
5.4 Results

5.4.1 Behavioral results

5.4.1.1 Accuracy. The ANOVA revealed main effects for Group ($F(1,44)= 9.81$, $p<.001$, $\eta_p^2 = .18$), and Learning Quarter ($F(3,132)= 136.08$, $p<.001$, $\eta_p^2 = .76$), with increasing accuracies between LQ1 vs. LQ2 ($t(45)= -12.4$, $p <.001$, $d= -1.82$), LQ2 vs. LQ3 ($t(45)= -4.68$, $p <.001$, $d= -0.69$), and LQ3 vs. LQ4 ($t(45)= -3.67$, $p <.001$, $d= -0.54$). In addition, a main effect for Feedback Condition ($F(1,44)= 25.88$, $p<.001$, $\eta_p^2 = .37$), and an interaction between Group and Feedback Condition ($F(1,44)= 8.24$, $p=.006$, $\eta_p^2 = .15$) was found (see Figure 5.2). Resolving this interaction showed that older adults had lower accuracies after non-social than social feedback ($t(23)=–5.48$, $p<.001$, $d=–1.12$), whereas this effect was not significant in younger adults ($p= .118$). Older adults had lower accuracies than younger adults after non-social ($t(36.2)= -4.18$, $p <.001$, $d= -1.22$), but not after social feedback ($p=.057$) (see Figure 5.3).

Figure 5.2

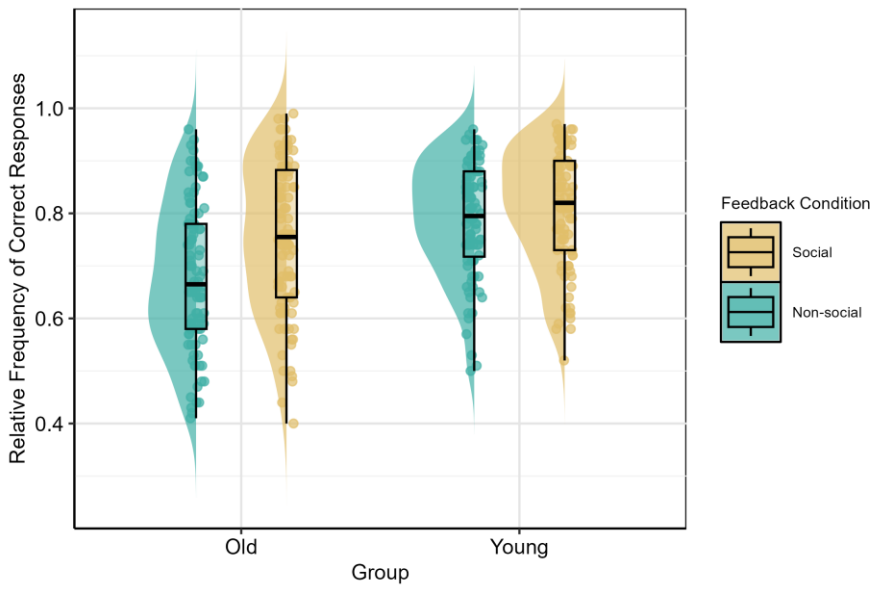
Mean reaction times and relative frequencies of correct responses



Note. Relative frequencies of correct responses and mean reaction times for both groups and both feedback conditions across four learning quarters (whiskers denote standard error of the mean).

Figure 5.3

Interaction for the accuracy between Group and Feedback Condition



5.4.1.2. Reaction Times. The ANOVA resulted in a main effect for Group ($F(1,44)= 72.40$, $p<.001$, $\eta_p^2 = .62$), with older adults reacting slower than younger adults. In addition, a main effect for Learning Quarter ($F(3,132)= 20.89$, $p<.001$, $\eta_p^2 = .32$), with decreasing reaction times between LQ1 vs. LQ2 ($t(45)= 3.00$, $p=.004$, $d= 0.44$) and LQ2 vs. LQ3 ($t(45)= 4.55$, $p<.001$, $d= 0.67$), but not between LQ3 vs. LQ4 ($p= .278$) was observed. Lastly, a main effect for Feedback Condition ($F(1,44)= 16.89$, $p<.001$, $\eta_p^2 = .27$), with slower reaction times after non-social than social feedback was found. Notably, no interaction with Feedback Condition reached significance (all *p*-values>.070).

5.4.2 Electrophysiological Results

5.4.2.1 Peak-to-Peak FRN. The peak-to-peak FRN (see Figure 5.4) ANOVA revealed a significant interaction between Group and Feedback Condition ($F(1,44)=10.22$, $p=.003$, $\eta_p^2= .19$). Older adults showed an enhanced peak-to-peak FRN after social as compared to non-social feedback ($t(23)= 2.08$, $p=.049$, $d= 0.43$), whereas younger adults had an enhanced peak-to-peak FRN after non-social than social feedback ($t(21)=-2.55$, $p=.019$, $d=-0.53$). Older adults additionally showed a larger FRN after social feedback than younger adults ($t(39.4)=-2.94$, $p=.005$, $d=-0.86$), whereas no group differences were found after non-social feedback ($p= .459$). No other effects including Group reached significance (all *p*-values >.053; see Figure 5.5).

Figure 5.4

FRN waveform at channel FCz for younger (left) and older (right) adults

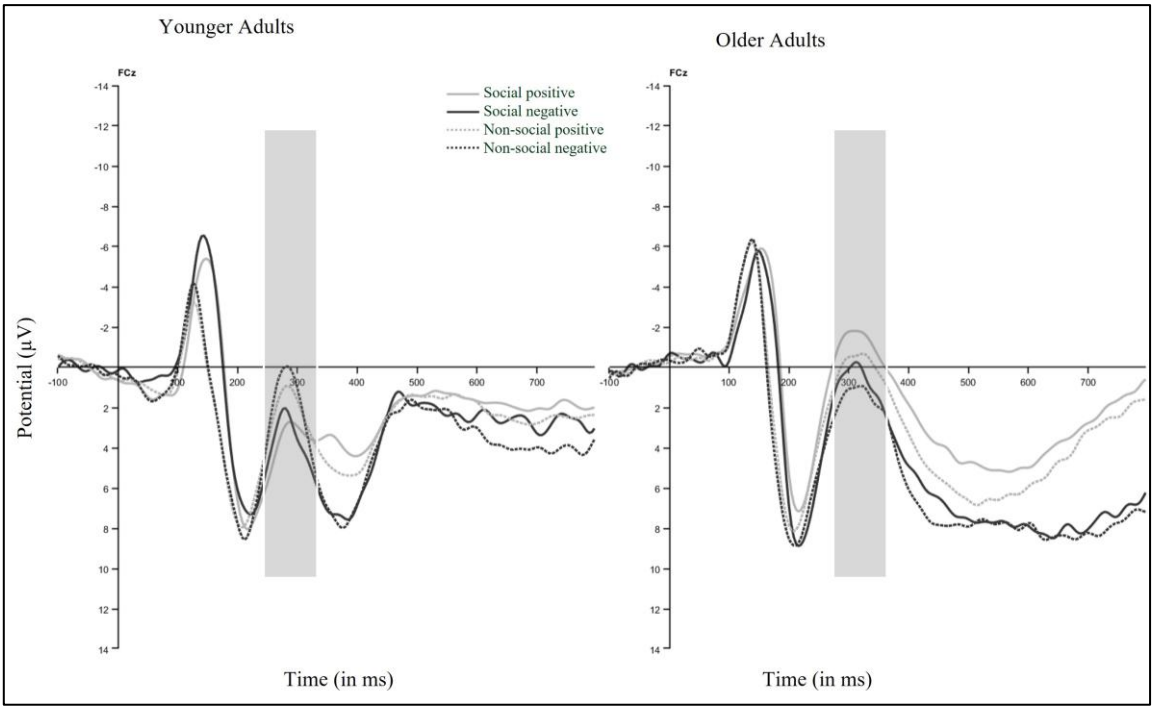
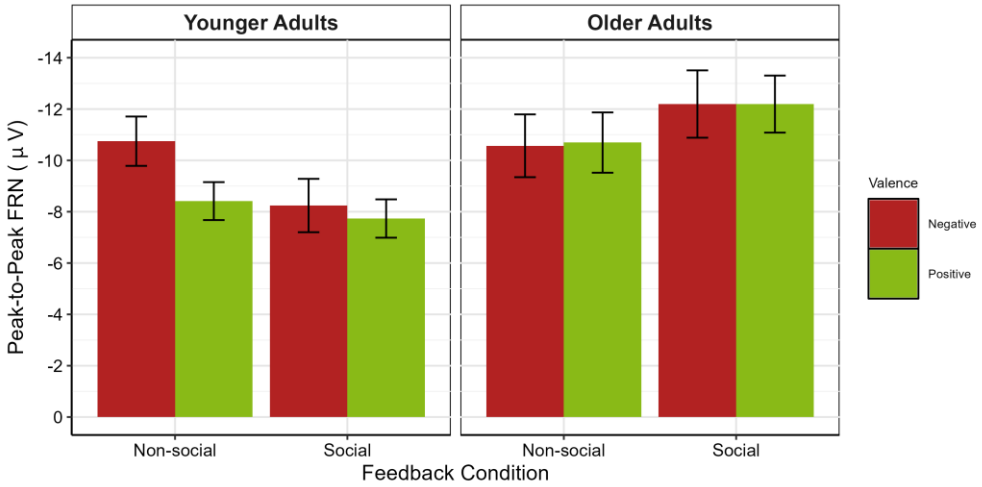


Figure 5.5

Bar plots illustrating the peak-to-peak FRN results

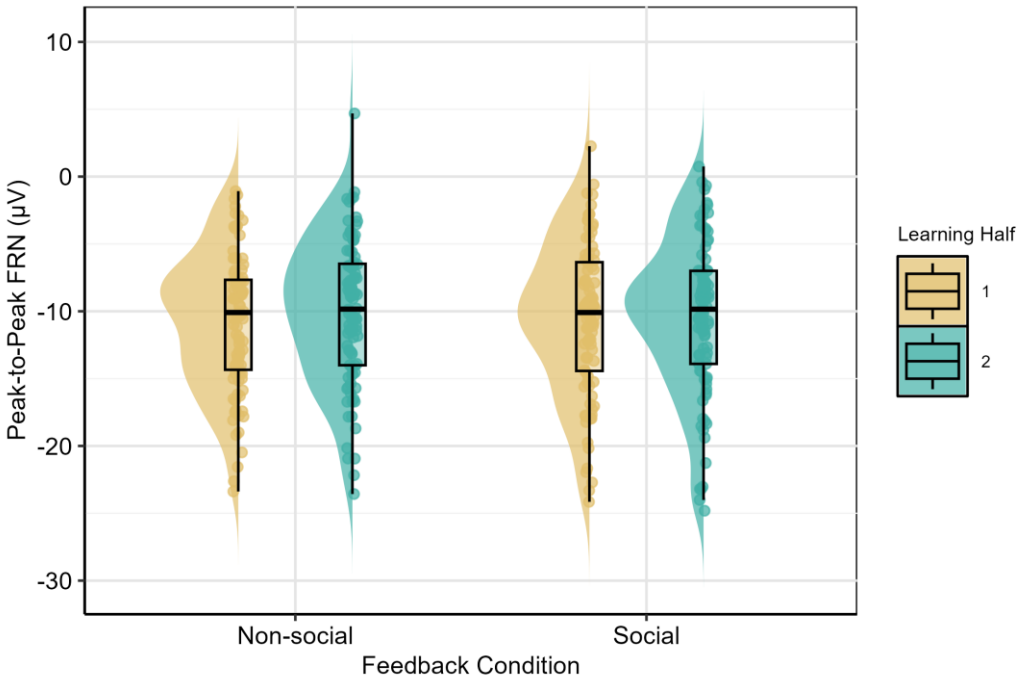


Note. Whiskers denote standard errors of the mean.

Because we could not detect a valence effect for the FRN in the preregistered analysis (p=.074), we decided to run an exploratory analysis by including an additional factor for Learning Half. This ANOVA resulted in a main effect for Group (F(1,44)=4.13, p=.048, η_p^2= .09) and an interaction between Group and Feedback Condition (F(1,44)=9.49, p=.004, η_p^2= .17). Additionally, a main effect for Valence (F(1,44)= 5.94, p=.019, η_p^2= .12) was found, indicating that the FRN component was larger for negative than for positive feedback. Moreover, a significant interaction between Feedback Condition and Learning Half (F(1,44)=4.15, p=.048, η_p^2= .08) was observed. While the peak-to-peak FRN amplitude declined after non-social feedback from Learning Half 1 to Learning Half 2 (t(45) = -2.72, p=.009, d=-0.40), no significant differences were found after social feedback (p= .686). There were no significant differences between non-social and social feedback in neither learning half (all p-values >.516, see Figure 5.6).

Figure 5.6

Peak-to-peak FRN after social and non-social feedback for each Learning Half



5.4.2.2 P3b. Examination of the mean P3b amplitude (see Figures 5.7 and 5.8) revealed main effects for Valence ($F(1,44)=26.56$, $p<.001$, $\eta_p^2= .37$), with larger amplitudes after negative compared to positive feedback, and Channel ($F(1,44)=26.82$, $p<.001$, $\eta_p^2= .38$). Further, interactions between Group and Channel ($F(1,44)=7.69$, $p=.004$, $\eta_p^2= .15$), Valence and Feedback Condition ($F(1,44)= 7.85$, $p=.008$, $\eta_p^2= .15$), Valence and Channel ($F(1,44)= 12.36$, $p<.001$, $\eta_p^2= .22$), and Feedback Condition and Channel ($F(1,44)= 4.50$, $p=.028$, $\eta_p^2=.09$) were observed.

Figure 5.7

P3b waveforms for both groups at electrode sites Fz, Cz, Pz

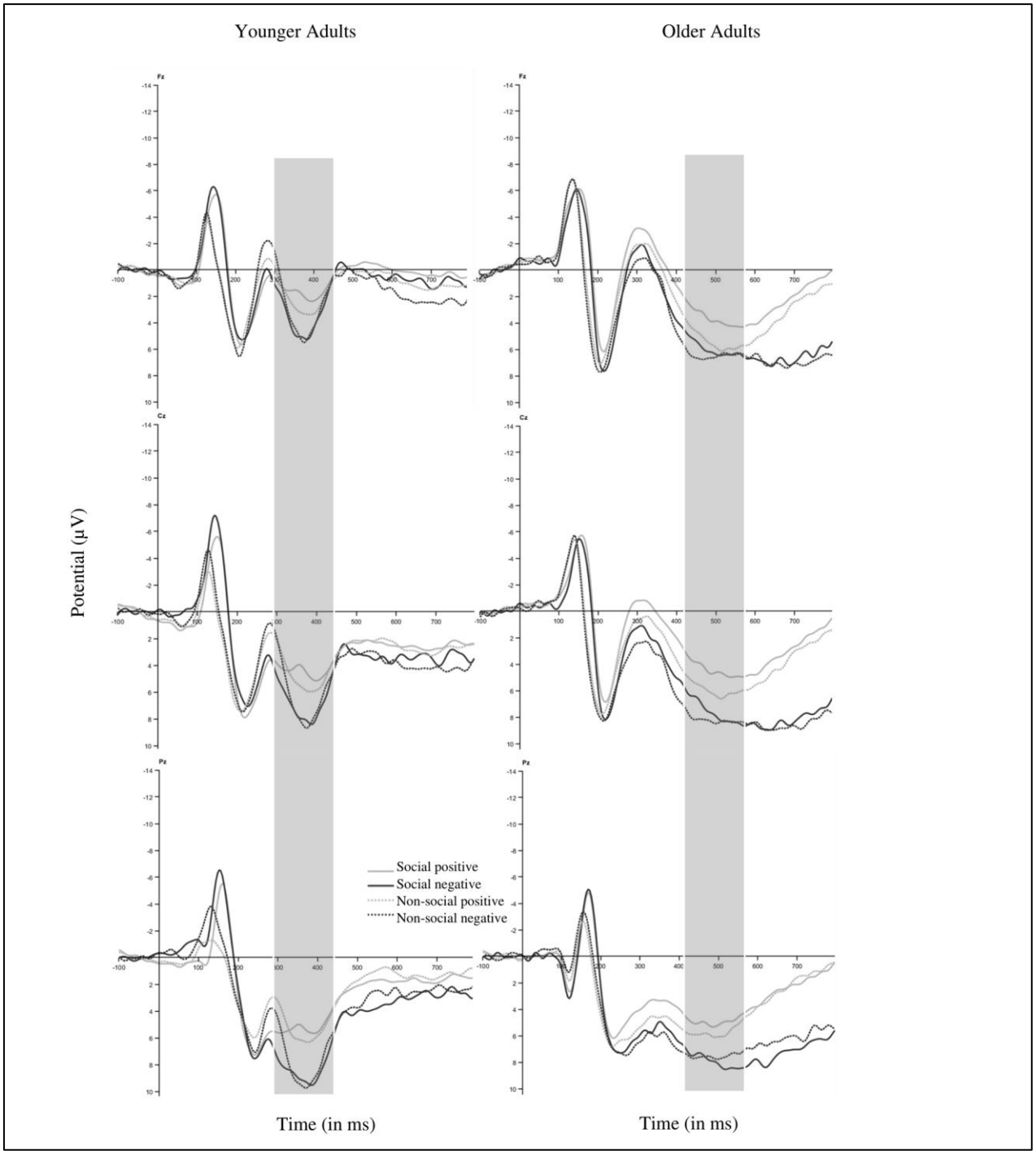
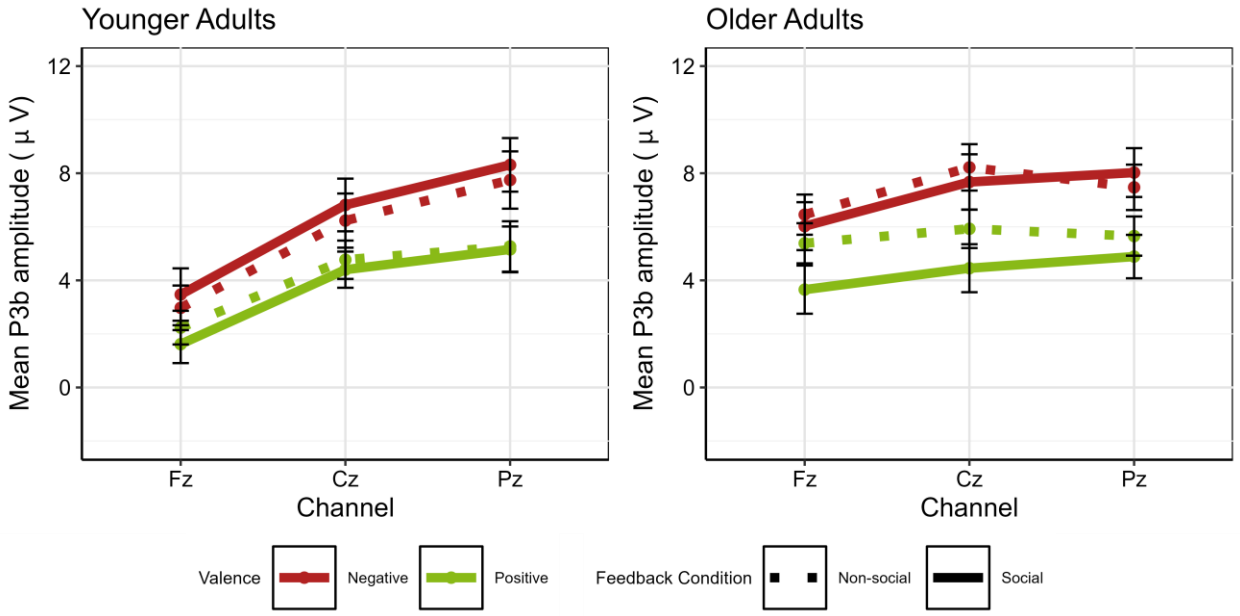


Figure 5.8

P3b graphs illustrating Valence, Feedback Condition and Channel locations for both groups

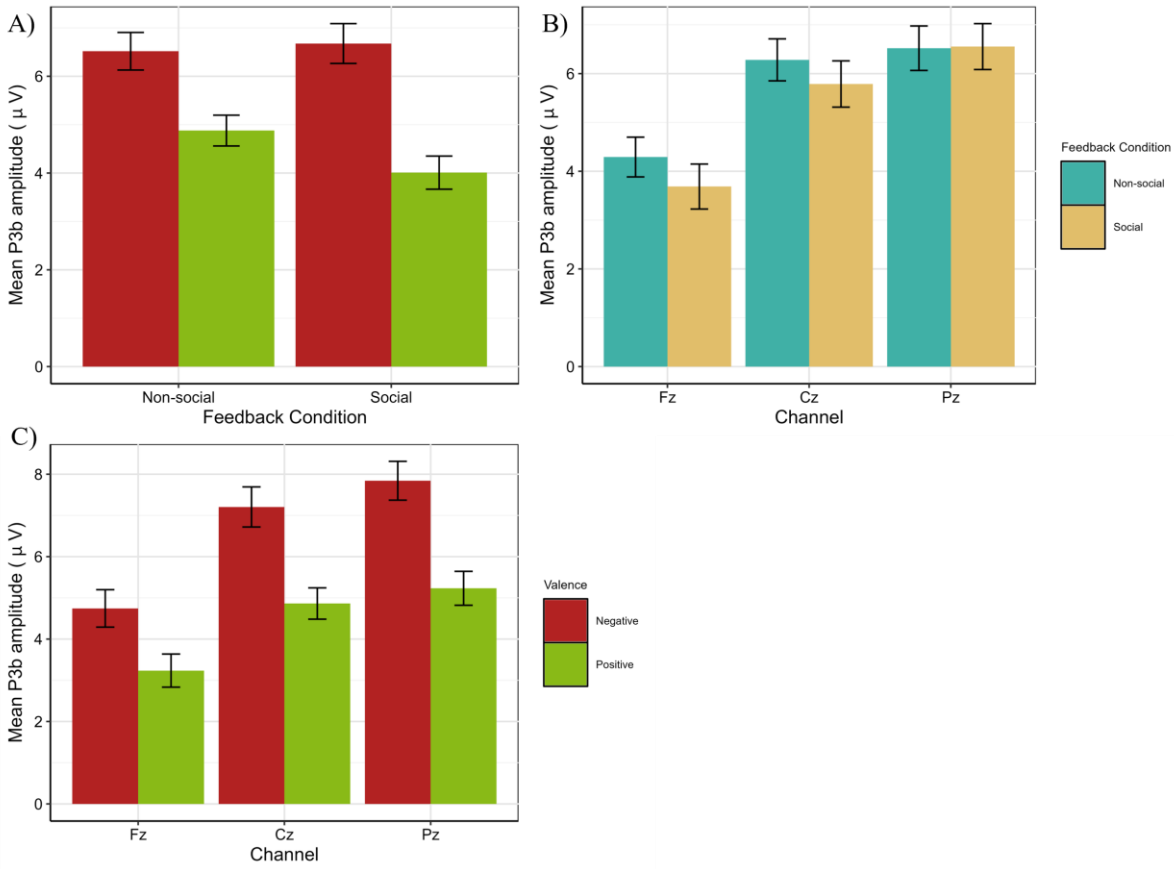


Note. Whiskers denote standard error of mean.

Resolving the interaction between Group and Channel showed that younger adults revealed significant amplitude differences between Fz vs. Cz ($t(21) = 6.20$, $p<.001$, $d= 1.32$), but not Cz vs. Pz ($p=.064$) for younger adults. The same result pattern was observed for older adults, with significant differences between Fz vs. Cz ($t(23) = 4.15$, $p<.001$, $d= 0.85$), but not between Cz vs. Pz ($p =.81$). In addition, mean P3b amplitudes were larger at frontal sites for older compared to younger adults (young vs. old at Fz:$t(43.7) = 2.71$, $p=.009$, $d= 0.79$; young vs. old at Cz and Pz: all p-values >.348).

Figure 5.9

Graphical illustration of the three two-way interactions



Note. Interaction between A) Feedback Condition and Valence, B) Channel and Feedback Condition, C) Channel and Valence. Whiskers denote standard error of mean.

Next, we resolved the interaction between Valence and Feedback Condition (see Figure 5.9A). Pairwise t-tests revealed that for negative feedback, no significant differences were found between non-social and social feedback (p =.619), whereas after positive feedback, non-social feedback elicited larger P3b amplitudes as compared to social feedback ($t(45)$ = 3.27, p =.002, d =0.48). However, negative feedback elicited larger P3b amplitudes compared to positive feedback after both feedback conditions (non-social: $t(45)$= 3.77, p<.001, d= 0.55; social: $t(45)$= 5.72, p<.001, d= 0.84).

Pairwise comparisons revealed that the interaction between Feedback Condition and Channel (see Figure 5.9B) can be explained by differences in topographical distributions. The mean P3b amplitude differed significantly between Cz vs. Fz for social as well as non-social feedback, with larger amplitudes at Cz (social: $t(45)= 6.74$, $p<.001$, $d= 0.99$; non-social: $t(45)= 6.49$, $p<.001$, $d= 0.96$)), and no significant amplitude differences between Cz vs. Pz for neither feedback condition (all p-values>.052). Only at frontal areas, non-social feedback elicited a larger P3b amplitude in contrast to social feedback ($t(45)= 2.38$, $p=.021$, $d= 0.28$), whereas at central and parietal areas no amplitude differences between the feedback conditions were found (Cz: $p=.132$, Pz: $p=.871$).

The last reported interaction between Valence and Channel (see Figure 5.9C) was due to significantly larger P3b amplitudes after negative as compared to positive feedback for all electrode positions (Fz: ($t(45)= 3.83$, $p<.001$, $d= 0.56$); Cz: ($t(45)= 4.84$, $p<.001$, $d= 0.71$); Pz: ($t(45)= 6.18$, $p<.001$, $d= 0.91$)). For negative as well as positive feedback, the mean P3b amplitude was larger for Cz in contrast to Fz (negative: $t(45) = 6.94$, $p<.001$, $d= 1.02$; positive: $t(45) = 5.63$, $p<.001$, $d= 0.83$), whereas no differences were found between Cz vs. Pz (all p-values >.081).

5.5 Discussion

The current study was designed to extend previous findings regarding the potential benefit of social feedback during learning in younger and older adults. To this end, we used unfamiliar hand gestures and similar complex abstract shapes colored in red and green (indicating incorrect vs. correct responses) as feedback stimuli in a probabilistic learning task. Interestingly, the results revealed that social information in feedback alone already led to a benefit in learning performance for both age groups and additionally led to a processing advantage in older adults in the early

processing stage. With regard to working memory updating, our findings suggest that social information in feedback is processed more efficiently in both age groups; however, feedback valence appeared as an even more relevant factor during this processing stage.

5.5.1 Learning Performance

All participants learned the stimulus–response associations, but older adults were slower than younger adults. While younger adults did not show additional learning benefits from social compared to non-social feedback, older adults reached accuracy levels comparable to younger adults when social feedback was provided. These results are in line with recent research using socio-emotional feedback, containing all three facets, such as sociality, emotionality and communicative meaning (Braunwarth & Ferdinand, 2026; Ferdinand & Hilz, 2020; Gorlick et al., 2013). As such, this study adds to the current literature by showing that age-related differences in learning can be reduced by providing feedback that only differs from abstract shapes by being conveyed via human hands. These findings provide evidence for the assumption that solely the sociality of feedback may already contribute to improved learning in their correct responses in older adults, while younger adults do not necessarily need this. Nevertheless, also younger adults used social feedback to learn faster.

Importantly, younger adults also showed faster learning when social feedback was provided, consistent with previous research using social feedback with communicative meaning (thumbs up vs. thumbs down, Pfabigan et al., 2019 or socio-emotional feedback (faces, (Braunwarth & Ferdinand, 2026; Braunwarth and Ferdinand, 2025; Hurlemann et al., 2010) in younger adults. The present findings are in contrast to a previous study using socio-emotional feedback with neutral and happy/disgusted faces presented in non-intuitive colors (yellow and blue, Ferdinand & Hilz,

2020), possibly due to a ceiling effect that reduced their benefit. However, also in a study by Hurlemann et al. (2010), younger adults learned better after socio-emotional than social feedback, reflected in either faces and green vs. red lights in a probabilistic selection task. These findings point to two potential explanations: (1) younger adults benefit from social feedback when sufficient cognitive capacity is available. Support for the former interpretation comes from our previous work demonstrating that, under conditions of low cognitive load, younger adults show an earlier advantage from socio-emotional feedback compared to high load (Braunwarth & Ferdinand, 2025) or (2) all individuals may benefit from feedback containing social information because such stimuli are biologically determined and evolutionary relevant, although this advantage may be less apparent in younger adults due to ceiling effects in learning tasks.

However, the behavioral data alone do not allow us to distinguish between these two explanations. Analyses of ERPs and the associated cognitive processes may help clarify whether the observed learning benefit reflects a basic bottom-up mechanism or is better accounted for by motivational theories of aging (Carstensen, 1991; Carstensen et al., 2006; Charles, 2010; Charles & Luong, 2013).

5.5.2 Detection of Unexpected Events

This study investigated whether younger and older adults differ in their processing of social feedback, potentially reflecting age-related differences in detecting unexpected events. Indeed, older adults show stronger expectancy violations after social as compared to non-social feedback (reflected in larger FRN amplitudes). This finding supports our assumption that purely social information (i.e., unfamiliar hand gestures), even without emotional information or communicative meaning, is already helpful for older adults in the early feedback processing stage. This pattern

differs from earlier findings. Previous research showed that older adults tended to display stronger expectancy violations for non-emotional than for socio-emotional feedback (faces), perhaps because neutral expressions were perceived as more unexpected or negative (Ferdinand & Hilz, 2020). Another study also found that older adults exhibited generally larger expectancy violations than younger adults, without sensitivity to the emotional intensity of the feedback (faces), possibly due to the subtle stimulus changes employed (weak vs. strong emotional intensity) (Braunwarth & Ferdinand, 2026). Overall, we could show that social stimuli engage age-related advantages. Previous studies using facial expression may have been unable to detect this advantage, possibly due to methodological challenges in creating adequate stimuli.

With the present modulation and the minimized emotional and communicative meaning in the social stimuli, we showed that older adults were more strongly drawn to social feedback in this fast initial feedback phase. Interestingly, the detection of unexpected outcomes after social feedback was more pronounced in older than in younger adults, an atypical pattern given that younger adults are usually more sensitive to expectancy violations (Eppinger et al., 2008; Hämmerer et al., 2011; Mies et al., 2011; Wild-Wall et al., 2009). This finding is further particularly surprising in light of the age-related decline in dopamine receptor density and dopamine firing efficiency (Bäckman et al., 2000; Bäckman et al., 2006; Lighthall et al., 2018). Thus, it seems that this early detection phase is sensitive to basic social information in older adults and may be rooted in fundamental biological mechanisms. Alternatively, motivational aging theories may account for this finding by proposing that older adults increasingly focus on emotionally and socially meaningful cues, which could lead to an enhanced neural response to social feedback (Carstensen, 1991; Carstensen et al., 2006; Charles, 2010; Charles & Luong, 2013).

Surprisingly, both assumptions do not explain the results of younger adults, as they showed enhanced expectancy violations in response to non-social feedback (abstract shapes). This finding is unexpected, as it suggests that non-social feedback was easier to process than social feedback in this probabilistic learning task. This pattern also does not align with the behavioral results, which showed that younger adults also benefited from social feedback. In an earlier study, we suggested that a potential benefit from socio-emotional feedback is dependent on the available cognitive capacity in younger adults (Braunwarth & Ferdinand, 2025), which may help explain the present findings. As Pfabigan et al. (2019) have demonstrated, feedback containing explicit communicative meaning can produce enhanced processing advantages in social feedback in younger adults. Therefore, more facets of socio-emotional feedback, such as emotionality or communicative meaning, may be needed to provoke early processing advantages of social stimuli at the same level as that achieved by older adults with unfamiliar hand gestures alone.

Further, our findings did not reveal the typical valence effect across the entire task, which is usually present during learning, with negative feedback eliciting larger FRN amplitudes than positive feedback (Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Miltner et al., 1997). However, when learning halves were included in the model, the expected pattern was observed: negative feedback elicited stronger FRN amplitudes. This likely reflects learning progression, as growing task knowledge reduces reliance on external feedback and thus the occurrence of expectancy violations, indexed by the FRN (Holroyd & Coles, 2002). As a result, valence differences are most pronounced early in learning and diminish over time, yielding a weaker overall valence effect across the task (Arbel & Wu, 2016; Braunwarth & Ferdinand, 2026; Ferdinand & Hilz, 2020).

The present findings suggest that feedback containing purely social information provides a processing advantage in older adults, which is also reflected in their learning performance. Younger adults, in contrast, do not seem to benefit from social feedback at this early stage of feedback processing. Yet, the detection of unexpected events is only one aspect of learning. Examining working memory updating as the next step may help clarify how social and non-social feedback shape context updating in older and younger adults.

5.5.3 Working Memory Updating

In the present study, we investigated the influence of social feedback on working memory updating in younger and older adults and how P3b topographies would be affected by valence and feedback condition.

We found that both younger and older adults showed a centro-parietal maximum in their working memory updating. The P3b usually shows a parietal maximum for similar tasks (Braunwarth & Ferdinand, 2025; Ferdinand & Hilz, 2020; Kamp et al., 2024; Polich, 2007). The more central activation for both age groups may be due to the fact that both feedback conditions were unfamiliar and therefore more demanding, resulting in a slightly broader scalp activation (Ferdinand, 2019; Reuter-Lorenz & Cappell, 2008; Segalowitz et al., 2001; Tregellas et al., 2006). Further, we observed a more frontal activation in older adults, suggesting the activation of additional frontal areas to compensate for age-related decline in working memory updating. This is a well-established finding and has also been shown for learning from feedback (Braunwarth & Ferdinand, 2026; Cabeza et al., 2002; Ferdinand, 2019; Ferdinand & Hilz, 2020; Friedman et al., 1997, 2007; Lubitz et al., 2017; Pietschmann et al., 2011; Reuter-Lorenz et al., 2000; West & Huet, 2020).

Our results additionally revealed that negative feedback resulted in enhanced working memory updating, which suggests that negative feedback was more relevant to perform the task and thus, to adapt behavior accordingly (Martín, 2012; Polich, 2004, 2007). This result corresponds to the literature using similar paradigms (Braunwarth & Ferdinand, 2026; Ferdinand, 2019; Ferdinand & Hilz, 2020; Frank et al., 2005; Kamp et al., 2024). The difference in the valence effect was larger in the social feedback condition, implying that processing social feedback was easier than non-social feedback (Pfabigan et al., 2019), which also matches the behavioral results.

In the current study, we expected that feedback containing purely social information would particularly support older adults' working memory updating during a probabilistic learning task. However, the findings primarily revealed that, in frontal areas, non-social feedback led to stronger activation, independently of age group. This pattern of findings is consistent with the notion that unfamiliar hand gestures may be processed more easily than non-social stimuli, potentially due to their biologically based nature, whereas non-social stimuli appear to require greater activation of frontal areas to extract their meaning and interpret the feedback (Braunwarth & Ferdinand, 2025; Ferdinand, 2019; Segalowitz et al., 2001). Surprisingly, after positive feedback, abstract shapes led to enhanced working memory updating compared to unfamiliar hand gestures. This finding could indicate that, even though no behavioral adaptation after positive feedback is required, abstract shapes may still require stronger processing due to their abstract nature (Polich, 2007). Another explanation could be that the interaction between valence and feedback condition may be partly driven by processes reflected at frontal electrode sites during the evaluation of abstract, non-social feedback. Whereas feedback valence modulated the updating of working memory across all electrode positions, indicating a general sensitivity to outcome valence, differences between feedback conditions were only observed at frontal recording sites. Thus, the observed interaction

may reflect the combination of a global valence-related modulation of working memory updating and an additional frontal effect associated with feedback condition. However, this interpretation should be treated with caution and requires further investigation in future studies.

Although we hypothesized that social feedback would be especially advantageous for older adults in facilitating working-memory updating, our findings did not support this expectation. Given that we attempted to isolate differences in sociality from emotional and communicative information by using unfamiliar, abstract hand gestures compared with abstract geometric shapes, the absence of a specific sociality effect on working memory updating in older adults may suggest that the motivation to strategically look for stimuli to enhance well-being in aging (Carstensen, 1991; Carstensen et al., 2006; Charles, 2010) is more affected by emotional or communicative (Schmitt et al., 2015) than by basic social content. This interpretation is consistent with previous findings demonstrating that socio-emotional feedback, such as facial expressions, enhanced updating of working memory more strongly in older adults (Braunwarth & Ferdinand, 2026; Ferdinand & Hilz, 2020).

In sum, we found no evidence that social information alone enhances working memory updating in older adults more strongly as compared to younger adults, suggesting that age-related motivational benefits likely depend on additional emotional or communicative information and that mere sociality is insufficient to provoke the updating of working memory. Nevertheless, our results indicate a general processing advantage for social feedback across age groups, consistent with a more automatic, biologically driven mechanism, whereas non-social feedback appears to require greater cognitive effort.

5.5.4 Strengths and Limitations

In the present study, we attempted to isolate the social aspect of feedback by reducing emotional and communicative meaning, allowing us to examine the effect of purely social information. To this end, we created social (abstract hand gestures) and non-social stimuli (abstract shapes) and conducted an online pre-study in which participants of various ages rated the stimuli on valence, arousal, familiarity, and complexity. However, the raters had a mean age of 33.5 years (range: 18–66), and were therefore considerably younger than the older adults who participated in the main experiment.

Another limitation of the present study is that participants in the main experiment were not asked to rate the stimuli themselves. Consequently, it remains unclear whether older adults interpreted the social stimuli as intended and whether such interpretations differ across age groups. Nevertheless, we found that social feedback was more beneficial than non-social feedback for learning performance, as reflected in the frequencies of correct responses.

This effect was more prominent in older adults. One possible reason for this is that younger adults may have reached a ceiling effect, which could limit the benefit they gain from social feedback. This could be investigated further by increasing the task difficulty.

Moreover, we demonstrated that the use of social feedback in feedback processing is age-dependent, but cannot be explained sufficiently by motivational aging theories. However, the influence of other components of socio-emotional feedback, such as emotional or communicative information, remains unclear and should be investigated in future research. Contrasting our results with those on facial feedback suggests that these additional components may also contribute to learning. Although research has been conducted primarily on facial stimuli and different emotions

in relation to developmental differences in learning, it would be interesting to investigate a different aspect of social stimuli in a future study, i.e., the role of communicative meaning in age-related learning to see whether it is the communicative aspect in feedback, which leads to a learning benefit. To this end, feedback containing social and communicative information could be compared with social stimuli that lack communicative content. This may help to further elucidate how different aspects of socio-emotional feedback contribute to learning across the lifespan, thereby guiding the development of effective cognitive trainings that help older adults remain active participants in society.

5.5.5 Conclusion

In the present study, both younger and older adults showed improved learning after social compared to non-social feedback, with older adults benefiting more. This advantage was also evident in working memory updating, indicating that the processing of social feedback is facilitated irrespective of age. Although we initially assumed that this benefit would be particularly pronounced in older adults due to motivational aging theories, our findings instead suggest that the processing of feedback is facilitated by basic social information, reflecting a more biologically grounded mechanism that is independent of age-related changes. Motivational influences in older adults may therefore rely more strongly on emotional or communicative elements of feedback than on pure social information. While social feedback supported older adults' neural detection of unexpected events, younger adults did not appear to benefit from social feedback at this early processing stage. They may require additional emotional or communicative information or greater cognitive capacity to effectively process such feedback. Overall, these findings provide nuanced insights into how distinct facets of socio-emotional feedback contribute to learning.

6 General discussion

The present thesis investigated the effects of socio-emotional feedback on learning in younger and older adults and the neural mechanisms underlying age-related differences in feedback-induced learning. In particular, the aim of this work was to gain a more detailed understanding of whether socio-emotional feedback can contribute to reducing age-related learning differences and which characteristics of such feedback are responsible for a potential learning benefit. At the time of this work, it was not yet clear whether age-related differences in learning from socio-emotional feedback primarily reflected increased working memory load in older adults or were driven by qualitative differences in the processing of feedback stimuli. Furthermore, it was not clear whether socio-emotional feedback conveyed through facial expressions could be interpreted as more neutral and therefore questionable whether precisely controlled socio-emotional feedback would still elicit learning advantages in older adults, and which characteristics of socio-emotional feedback may lead to these advantages on a behavioral and electrophysiological level. To examine feedback processing in more detail, the thesis focused on two core mechanisms that are assumed to be closely related to behavioral adaptation during learning: the detection of unexpected events and the updating of working memory. These mechanisms were operationalized using established electrophysiological markers, namely the FRN and the P3b component. Across three experiments, the present thesis aimed to disentangle these factors in a systematic manner. In Study 1, working memory load was manipulated in younger adults to investigate how cognitive load influences the use of socio-emotional feedback during probabilistic learning. Study 2 examined whether varying intensities in emotionality of socio-emotional feedback modulate learning performance, with a particular focus on potential benefits for older adults. Finally, Study 3 investigated whether mere sociality of feedback without emotional content or learned

communicative meaning would be sufficient to show age-related benefits in learning. Across all studies, behavioral markers of learning, such as accuracy and reaction times, were combined with the above-mentioned electrophysiological markers to capture the neural mechanisms supporting feedback-induced learning. Together, these data provide a comprehensive account of how socio-emotional feedback interacts with behavioral adaptation across the adult lifespan. The following chapter first summarizes the key findings of each study and then integrates them within a broader theoretical framework. Subsequently, remaining open questions, limitations, and implications for theory and practice are discussed.

6.1 Summary of main findings

At the behavioral level, all three studies consistently showed superior learning performance from socio-emotional in contrast to non-emotional or non-social feedback. While younger adults needed more practice in performing the probabilistic learning task and therefore benefitted later from socio-emotional feedback, older adults already benefitted in the early stages of learning. Additionally, they showed comparable learning performance after socio-emotional feedback than their younger counterparts concerning learning performance measures such as accuracy and reaction times. This pattern was observed across different manipulations of socio-emotional feedback characteristics, including emotionality (Studies 1 and 2) and sociality with reduced emotional and communicative meaning (Study 3), indicating that feedback containing socially relevant information can support learning across the adult lifespan, not only limited to older adults.

At the level of early feedback processing, socio-emotional (Studies 1 and 2) and social feedback (Study 3) influenced the detection of unexpected events, with effects differing across age groups and feedback contexts. In older adults, enhanced responses to the detection of unexpected

outcomes were observed across studies when feedback contained socio-emotional or social information. In Study 2, older adults showed larger FRN amplitudes than younger adults irrespective of feedback condition, albeit both conditions consisted of socio-emotional feedback, whereas in Study 3, FRN amplitudes in older adults were larger following social compared to non-social feedback. Together, these findings indicate that early feedback processing remains preserved with age and may even be heightened in the presence of socially or emotionally salient feedback.

In younger adults, early feedback processing appears to be more specific. While Study 1 revealed an enhanced detection of unexpected events under socio-emotional feedback independently of task difficulty, younger adults did not show increased FRN amplitudes in response to social or socio-emotional feedback in Study 2 and 3. Especially, in Study 3, younger adults processed non-social feedback stronger than social feedback.

Age-related differences were observed more clearly at later and thus more evaluative stages of feedback processing associated with working memory updating. Across studies, variations in working memory load and feedback characteristics affected the topographical distribution of the neural correlates of working memory updating, while leaving the overall magnitude of the response largely unaffected. High task difficulty or reduced feedback interpretability were associated with a shift toward more frontal activation patterns, whereas conditions that facilitated feedback interpretation, such as explicit valence or distinguishable socio-emotional feedback, elicited more typical posterior updating activity. Crucially, this frontal shift was not restricted to older adults: younger adults exhibited similar patterns under high working memory load, indicating that such shifts reflect compensatory mechanisms in response to increased cognitive demands rather than age-specific effects, which underline the CRUNCH-model (Reuter-Lorenz & Cappell, 2008). The

frontal shift occurs so that performance can be maintained, resulting in a more anterior brain activation.

Taken together, the results across all three studies demonstrate that socio-emotional and social feedback can support learning by enhancing both early feedback evaluation and later working memory updating processes. Interpretations, as well as embedding the current findings into theoretical concepts and theoretical and practical implications will be discussed in the following paragraphs.

6.2 Discussion of main findings

Because each study has been discussed in detail in their respective chapter and to avoid repetition, The most important findings within the studies are synthesized and embedded into theoretical concepts to address the primary objectives of the dissertation.

6.2.1 Socio-emotional feedback as a reinforcer of learning in older adults

The behavioral evidence for socio-emotional feedback as a reinforcer in older adults in the present thesis is derived from Study 2 and Study 3, as older adults were not included in Study 1. Across these two studies, socio-emotional feedback was consistently observed as an effective facilitator of learning in older adults within a probabilistic learning task. Independent of the specific operationalization of feedback characteristics, older participants showed higher accuracy and faster reaction times when feedback conveyed socio-emotional information compared to non-emotional or non-social feedback. This finding is particularly noteworthy because the probabilistic learning task remained unchanged in Study 3, and feedback stimuli were intuitively colored according to their valence. Thus, the observed learning benefits cannot be attributed to differences in task structure, but most likely reflect the social or socio-emotional nature of the feedback itself. In

addition, older adults were as accurate as younger adults when presented with strong emotional facial expressions or unfamiliar hand gestures. Nevertheless, younger adults outperformed older adults in terms of reaction times. This could be discussed in light of a slower processing speed and generalized slower reaction time in older adults (Salthouse, 2010). However, to avoid this bias, we used an adaptive reaction time procedure, which led to a more objective accuracy measure and therefore could show a learning benefit independently of the age-related differences (Eppinger et al., 2008).

This pattern of enhanced benefit from socio-emotional and social feedback in older adults replicates and extends previous findings demonstrating that learning performance is disproportionately affected by socially or emotionally meaningful feedback in older adults. Earlier work by Ferdinand and Hilz (2020) showed that facial expressions as feedback reduced age-related learning deficits compared to neutral feedback, and similar conclusions were drawn from studies on rule learning using facial versus abstract feedback (Gorlick et al., 2013). The present results corroborate these findings while broadening their scope: learning benefits were observed not only for emotionally expressive facial feedback, but also for feedback that was reduced to its basic social component, as demonstrated in Study 3. Thus, socio-emotional feedback does not act as a reinforcer solely because of emotional expressiveness but appears to draw its effectiveness from the broader relevance of socially embedded evaluative information, especially for older adults.

In contrast, the behavioral effects of socio-emotional feedback in younger adults were less consistent and generally smaller in magnitude. One possible explanation for this discrepancy relates to overall task demands. For younger adults, the probabilistic learning task may have been relatively easy, enabling them to achieve high performance based mainly on stimulus–response learning even without the aid of socio-emotional feedback. Under these conditions, socio-

emotional information may provide little additional behavioral benefit due to ceiling effects. This interpretation is in line with the results of Study 1, which showed that younger adults' learning performance improved steadily across all feedback conditions. Effects of socio-emotional feedback on reaction times emerged only after learning performance had largely stabilized in the difficult task condition. This pattern suggests that younger adults benefited from socio-emotional feedback primarily once the correct stimulus–response associations had already been learned. In the easy task condition, these associations were likely acquired early in the learning phase, which may explain why socio-emotional feedback did not produce additional improvements during learning itself. The reduced attenuation of socio-emotional feedback effects during the learning phase should therefore not be interpreted as evidence that such feedback is irrelevant. Rather, it may indicate that task demands compete with the processing of socio-emotional feedback information in younger adults. These arguments can be supported by the findings of Hurlemann et al. (2010), in which the social reinforcer, in the form of facial feedback, led to a higher accuracy in an item-category judgement task compared to red and green lights, and by the findings from Study 2, where the intensity of emotional facial expressions also gave younger adults a benefit in learning performance based on reaction times and accuracy. In contrast, Study 3 did not reveal any learning advantage from social feedback in younger adults in accuracy, suggesting that basic social stimuli in a relatively easy task do not give any learning benefit compared to non-social feedback, whereas the sociality of feedback does have an influence on the time for producing correct responses.

These findings suggest that socio-emotional feedback may influence learning differently across age groups. Specifically, socio-emotional feedback may support learning more automatically in older adults, whereas younger adults may benefit from it primarily when sufficient

cognitive resources are available or when feedback includes more than the social component of socio-emotional feedback.

Importantly, although the behavioral data clearly demonstrate that socio-emotional feedback enhances learning outcomes in older adults, they do not allow conclusions about valence-specific learning mechanisms. Accuracy and reaction times reflect overall learning success, but they do not capture how positive and negative feedback are differentially weighted or used to update behavior. This is particularly relevant in light of theoretical accounts proposing motivational shifts in aging, including the positivity effect, which suggest that older adults may preferentially learn from positive feedback (Carstensen, 1991; Charles & Piazza, 2024; Mather & Carstensen, 2005; Reed et al., 2014). While such valence-specific hypotheses are theoretically well motivated, investigating them would require trial-by-trial analyses or computational modeling approaches and a more comparable percentage of positive and negative feedback, for example by using time-estimation tasks, that were beyond the scope of the present dissertation (Ferdinand & Kray, 2013; Ferdinand & Opitz, 2014; Ullsperger et al., 2014; Ullsperger, 2024).

The decision to refrain from explicit valence-specific learning analyses (i.e., analyses that separately model learning from positive versus negative outcomes) was therefore both conceptual and methodological, as our approach instead focused on overall learning dynamics and age-related differences. Moreover, the probabilistic task design was optimized to ensure stable learning and sufficient trial numbers for reliable ERP analyses (Luck & Gaspelin, 2017; Luck & Kappenmann, 2012). Therefore, negative feedback was reduced over the course of the experiment, which is why this question could not have been additionally investigated.

Taken together, the behavioral findings support the conclusion that socio-emotional feedback acts as a support for learning in older adults, especially in the relative frequency of correct responses, reducing age-related performance differences and promoting more efficient learning. However, behavioral markers alone cannot disentangle whether these effects arise from changes in expectancy violations, or the gating of feedback information into working memory. According to the cognitive control framework proposed by Braver and Barch (2002), such age-related differences are likely rooted in alterations of control mechanisms regulating the updating and maintenance of task-relevant representations, which may be linked to changes in dopaminergic functioning. For this reason, the present dissertation focuses on behavioral performance measures in combination with neurophysiological markers, which allows for a theoretically coherent investigation of how socio-emotional feedback shapes learning across age groups.

6.2.2 Performance monitoring as a motivationally modulated process in aging

Early outcome detection is commonly conceptualized as a rapid detection mechanism of unexpected events, with the FRN serving as a neural marker of expectancy violations in performance monitoring. Within this framework, age-related differences in FRN amplitude have often been interpreted as reflecting reduced dopaminergic signaling and diminished prediction-error precision in aging (Nieuwenhuis et al., 2002; Wild-Wall et al., 2009). While this interpretation is supported by substantial neurobiological evidence (Bäckman et al., 2010; Bäckman & Farde, 2005), the present findings of this work suggest that the functional role of early outcome detection across the adult lifespan cannot be fully understood within a purely deficit-oriented framework.

The present results indicate that, while the FRN continues to reflect the detection of expectancy violations, the magnitude of this detection signal is shaped by contextual and

motivational relevance. In this sense, the FRN indexes not only whether an outcome is unexpected, but also how strongly this unexpectedness is weighted within the detection system. This is evidenced by feedback-processing studies in younger adults, showing that reward magnitude or delayed feedback modulated the FRN, possibly due to increases or decreases in motivation (Paul et al., 2020; Weismüller & Bellebaum, 2016).

This interpretation is further supported by evidence from Study 2 and Study 3. In Study 2, older adults exhibited robust FRN responses to facial feedback irrespective of emotional intensity. Rather than indicating insensitivity to emotional gradation, this pattern suggests that socio-emotional feedback per se was sufficient to engage early detection mechanisms. Once feedback exceeded a threshold of socio-emotional relevance, subtle variations in intensity no longer modulated early outcome processing. Consistent with this account, motivational relevance appears to operate as an early-stage amplification mechanism, boosting detection signals for meaningful feedback without further scaling with intensity (Pfabigan et al., 2011).

Study 3 further strengthened this account by demonstrating that purely social feedback, even in the absence of emotional expression and explicit communicative meaning, elicited enhanced FRN responses in older adults compared to non-social feedback. This finding indicates that modulation of early outcome detection in older adults does not rely exclusively on emotional intensity, but can be driven by social relevance alone. Together, these results suggest that socio-emotional and social feedback increase early detection signals in older adults, resulting in preserved or even enhanced FRN amplitudes despite age-related neurobiological constraints and inviting a broader and more differentiated interpretation of early feedback detection in aging, one that emphasizes adaptive reorganization rather than uniform decline (Ferdinand & Hilz, 2020).

From a lifespan perspective, these findings align with models that conceptualize cognitive aging as an interaction between biological limitations and adaptive reorganization (Reuter-Lorenz & Park, 2014). Within the STAC-R model, neural changes associated with aging are not understood as fixed deficits, but as conditions under which compensatory mechanisms can be flexibly recruited depending on the conducted intervention. Based on the present results, socio-emotional information in feedback may function as a compensatory scaffold within the framework, facilitating early feedback processing in older adults.

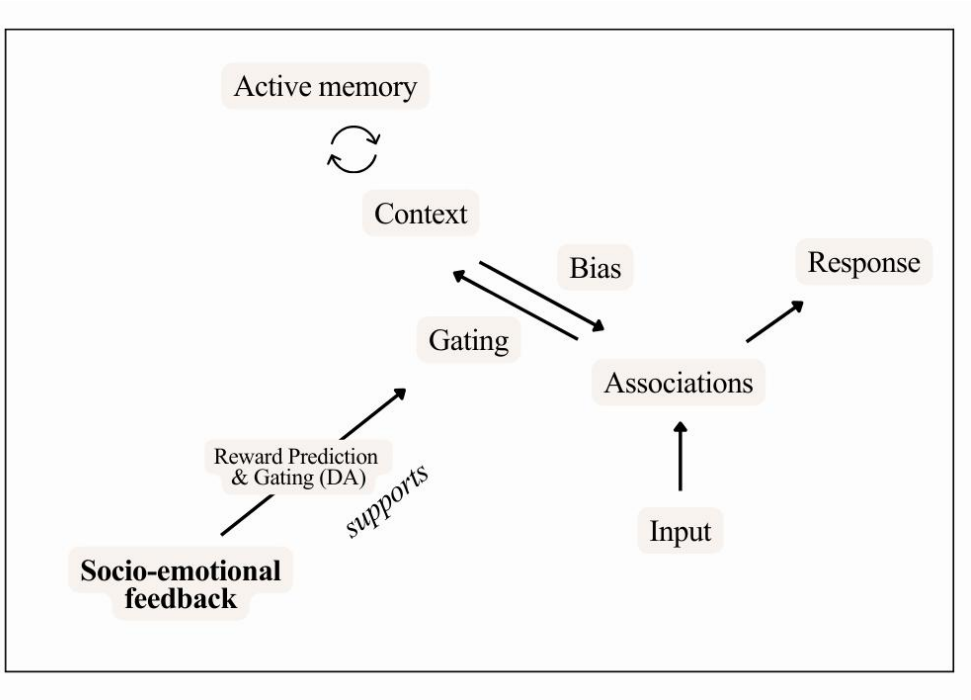
The SST and SAVI model both further propose age-related shifts in motivational priorities across the lifespan, such that emotionally and socially meaningful information become increasingly salient in older adults (Carstensen, 1991, 2021; Charles, 2010; Charles & Luong, 2013; Charles & Piazza, 2024). In this sense, socio-emotional feedback may increase the subjective relevance of outcome information and amplifies motivational shifts (Carstensen, 1991; Charles, 2010). These shifts then may enhance early detection signals, allowing prediction errors to be processed more robustly despite the theoretically grounded reduced dopaminergic signal quality (Bäckman et al., 2000; Bäckman et al., 2010).

This interpretation is also compatible with the DA gating model of cognitive control proposed by Braver and Barch (2002). According to this model, phasic dopamine signals regulate when outcome information gains access to working memory representations. Age-related reductions in dopaminergic efficiency may compromise this gating mechanism, making it more difficult to determine which feedback signals should be integrated for learning. The present findings could indicate that motivational relevance may influence early outcome processing by modulating dopaminergic gating mechanisms. Socio-emotional feedback may increase dopaminergic responsiveness due to the enhanced motivational nature of feedback at the stage of

outcome detection, thereby amplifying the DA signals, which are responsible for gate opening and enabling the transmission of RPE signals even when signal precision is diminished. In this way, motivational factors may complement dopaminergic gating by shaping the effectiveness of early detection signals.

Figure 6.1

Adapted cognitive control model



Note. Modified model from Braver and Barch (2002) showing the location where socio-emotional feedback leads to enhanced gating mechanisms.

Crucially, the present findings further suggest that the modulation of the FRN in older adults is not driven exclusively by bottom-up processing of socio-emotional feedback, but also by top-down influences related to motivational priorities (Luft, 2014). Age-related motivational shifts may shape expectations about the relevance of feedback before outcome presentation, thereby preconfiguring early systems. From this perspective, socio-emotional feedback does not merely

elicit stronger neural responses due to its perceptual characteristics, but engages top-down processes that enhance the early detection mechanism at the moment expectancy violations are registered.

Such top-down modulation is consistent with the assumption that motivational relevance biases early detection processing by amplifying RPE signals when feedback aligns with current goals and priorities (Severo et al., 2020; Walentowska et al., 2016). In older adults, socio-emotional feedback may therefore strengthen FRN responses by increasing the anticipated relevance of feedback events, effectively preparing the monitoring system to respond more strongly to unexpected outcomes. This interpretation extends both scaffolding accounts of cognitive aging and dopaminergic gating models by highlighting motivationally guided top-down processes as a key mechanism regulating early outcome detection (Reuter-Lorenz & Park, 2014; Braver & Barch, 2002).

In contrast, the pattern observed in younger adults across Study 1 to Study 3 points to a qualitatively different early feedback processing. While younger adults exhibited FRN sensitivity to socio-emotional feedback under certain conditions, these effects were inconsistent and did not systematically translate into behavioral learning advantages. The findings from Study 1 suggest that early outcome detection in younger adults is primarily independent of cognitive demands such as enhanced working memory load, but may be more shaped by feedback characteristics and task structure. While socio-emotional feedback in the form of faces with a strongly different neutral condition (scrambled faces) led to a processing advantage, this effect vanished after controlling more carefully for feedback stimuli by morphing the images, without additionally intuitively color coding them and conducting a pre-study. In Study 3, non-social feedback in the form of abstract shapes led to enhanced processing in contrast to the more natural hand gestures. These findings

can be explained by (1) the task, which may have been too easy and therefore younger adults did not need to rely on the external feedback per se. However, we did not find a task difficulty effect in Study 1 for the early detection phase. Therefore, a more plausible explanation is (2) that age-related differences are more likely to reflect variations in motivational priorities (Ferdinand & Czernochowski, 2018). For example, younger adults may place greater motivational emphasis on monetary rewards, which may modulate feedback processing in a similar way as social feedback in older adults (Flores et al., 2015; Schmitt et al., 2015).

The present findings point to differences in the determinants of early outcome detection across younger and older adults. While the FRN continues to reflect the detection of unexpected outcomes in both younger and older adults, the extent to which this detection signal is expressed appears to be increasingly shaped by motivational relevance of socio-emotional information during aging. This pattern may reflect an adaptive reweighting of early detection mechanisms, which may provide a mechanistic link between motivational theories of aging and neurocognitive models of feedback-induced learning.

6.2.3 Working memory as a bottleneck in learning

The present thesis demonstrates that socio-emotional feedback can support learning across adulthood, but that its effectiveness critically depends on the ability to integrate feedback into working memory representations. Across all three studies, differences in feedback-induced learning were not characterized by uniform age-related differences, but by systematic variations in how working memory updating was regulated under differing task demands and feedback characteristics. This pattern suggests that working memory updating represents a central bottleneck through which learned information must pass in order to influence adaptive behavior, and that

socio-emotional feedback appears to facilitate the integration of feedback information into working memory representations.

The findings of the present thesis indicate that working memory updating is flexibly reorganized by recruiting different neural resources in response to task demands rather than being uniformly reduced with age. Under high working memory load, younger adults in Study 1 exhibited a frontal shift in P3b topography that closely resembled the pattern observed in older adults across Studies 2 and 3. Such frontal recruitment is commonly interpreted as a compensatory response when task demands exceed available processing resources and aligns with compensatory frameworks such as CRUNCH and PASA within the STAC-R model (Davis et al., 2008; Reuter-Lorenz & Cappell, 2008). Importantly, increased task difficulty primarily altered the spatial distribution of the P3b rather than its overall amplitude, suggesting that frontal compensation is reflected in how neural resources are allocated rather than in the magnitude of working memory updating per se.

Conversely, when working memory load was low, feedback information was cognitively accessible, and easily processable with a clear interpretation, younger adults consistently showed a parietal maximum of the P3b across all studies, in line with classical context-updating accounts (Polich, 2007). This parietal distribution indicates efficient integration of feedback into working memory without the need for compensatory recruitment. Together, these findings demonstrate that frontal recruitment is not an obligatory feature of either aging or feedback processing but is observed when cognitive demands exceed available resources (Kok, 2001; Polich, 2007; Reuter-Lorenz & Cappell, 2008).

In older adults, feedback characteristics played a critical role in modulating compensatory recruitment during working memory updating. In Study 2, older adults showed a parietal P3b maximum when feedback consisted of morphed facial expressions, suggesting that working memory updating mechanisms remain responsive to rich socio-emotional information.

In contrast, the more centro-parietal activation observed in Study 3 likely reflects increased cognitive effort when feedback consisted of unfamiliar hand gestures and abstract shapes, which provided less immediately accessible information for working memory updating, despite being colored in intuitive positive (green) and negative (red) tones. This finding, however, is not age-specific, but rather a consequence of the abstract shapes. While participants could have ignored the shown stimuli and only focused on the colors, additional social information conveyed through unfamiliar hand gestures may, nevertheless, facilitated processing in contrast to the unfamiliar abstract shapes, supporting this interpretation.

Older adults showed enhanced working memory updating in Study 2 when feedback contained strong emotional expressions, replicating earlier findings and supporting motivational aging theories (Ferdinand & Hilz, 2020; Carstensen, 1991). These effects were present despite missing compensatory frontal activation, suggesting that especially those facial emotional expressions can also serve as compensatory support, which does not need additional resources to be integrated in working memory representations. In contrast, the absence of a comparable effect in Study 3 suggests that basic social information alone may not be sufficient to engage motivational mechanisms at the level of working memory updating. While facial expressions appear to provide sufficient socio-emotional richness to support compensatory scaffolding, social stimuli lacking affective content, may primarily influence earlier stages of feedback processing rather than subsequent updating. With regard to theoretical frameworks, the present findings suggest a

refinement of the STAC-R model, indicating that compensatory scaffolding is not solely driven by capacity limitations, but is also modulated by characteristics of the input that determine the extent to which compensatory mechanisms are engaged in older adults (Reuter-Lorenz & Park, 2014).

A central question of the present thesis was whether younger adults would benefit from socio-emotional feedback in a manner comparable to older adults when approaching their processing limits. While Study 1 suggested enhanced working memory updating in younger adults after socio-emotional feedback across task conditions, this effect could not be replicated in Studies 2 and 3 using more controlled and perceptually comparable stimuli. These latter findings converge with previous evidence showing that younger adults primarily rely on feedback valence rather than socio-emotional characteristics when updating their working memory representations (Ferdinand & Hilz, 2020). One plausible explanation is that under low working memory load, additional social or emotional information is not required for effective updating, as valence alone provides sufficient task-relevant information. This, however, is in contrast with other paradigms, such as time-estimation tasks, in which also younger adults used social feedback to update their working memory more efficiently (Pfabigan et al., 2019; Pfabigan & Han, 2019). However, time-estimation tasks are typically more difficult and require permanent behavioral adjustment. Therefore, additional socio-emotional information may be processed to facilitate outcome processing during time estimation, even in younger adults.

Conceptually, these findings indicate that the benefit of socio-emotional feedback for working memory updating may neither be a simple function of age nor of working memory load. Instead, it depends on the interaction between task demands and feedback characteristics. By systematically manipulating working memory load and feedback properties across studies, the present work advances existing compensatory accounts by demonstrating that working memory

updating is a dynamically regulated bottleneck that mediates how socio-emotional feedback supports learning across adulthood.

6.2.4 Disentangling socio-emotional feedback facets in older adults

The present thesis provides first evidence that socio-emotional feedback facilitates learning in older adults, while at the same time demonstrating that this facilitation cannot be attributed to a single, uniform mechanism and is also dependent on the feedback characteristics. The findings indicate that different facets of socio-emotional feedback selectively support distinct stages of feedback processing in older adults. Disentangling these facets is therefore essential for understanding how socio-emotional information contributes to learning in later adulthood and with the present thesis and two included studies, a first step towards the disentangling has been provided.

Across the studies, older adults consistently showed behavioral benefits from feedback containing socio-emotional information, irrespective of whether this information was conveyed through emotionally expressive facial feedback or through more reduced social feedback in the form of unfamiliar hand gestures. This is an extension to recent findings that socio-emotional feedback, in its broadest sense, functions as a meaningful learning signal for older adults (Ferdinand & Hilz, 2020; Gorlick et al., 2013). Nashiro et al. (2011), on the other hand, could not detect these emotionality effects in the reversal learning task, but this may be due to the learning mechanisms in reversal learning. For tasks, in which learning actually takes place, these feedback types seem to be advantageous compared to their non-emotional or non-social antagonists. However, neural data revealed that not all facets of socio-emotional feedback contribute in the same way to different processing stages.

With regard to early outcome detection, the findings suggest that social relevance constitutes a sufficient condition to engage early detection mechanisms in older adults. In Study 3, purely social feedback, devoid of emotional expression and explicit communicative meaning, elicited enhanced detection of unexpected events. This pattern may indicate that early detection in older adults is highly sensitive to the social significance of feedback, even when emotional intensity is minimal (Ferdinand & Hilz, 2020; Legaz et al., 2022). There is sparse evidence for older adults, but one possible explanation is that social feedback in the form of unfamiliar hand gestures already serve as a reward signal and therefore may modulate the early detection phase possibly due to increases in DA distribution in the ACC (Samanez-Larkin et al., 2014). Importantly, this suggests that the initial registration of expectancy violations does not require emotionally rich input, but can be triggered by basic social stimuli alone due to a biologically determined nature in this fast detection.

In contrast, later stages of feedback processing that involve the integration of outcome information into working memory representations appear to place higher demands on the qualitative characteristics of the feedback. While emotionally expressive facial feedback in Study 2 supported working memory updating in older adults, reduced social feedback in Study 3 did not produce comparable age- effects at this stage. This dissociation suggests that, although social relevance alone may be sufficient to modulate early detection processes, the effective integration of feedback into working memory in older adults requires additional emotionality or communicative information to be comparably effective. Emotional expressiveness or communicative clarity may therefore be particularly relevant for determining whether feedback information is not only registered, but also maintained and utilized for subsequent behavioral adaptation. A possible explanation for this assumption is that emotional expressiveness or

communicative meaning may function as a scaffolding mechanism, supporting the stabilization of internal representations in working memory and rendering them less susceptible interference due to their motivational aspects (Carstensen et al., 1999, 2010; Carstensen, 1991). In addition, while social feedback may be registered in an early and fast process and may push DA firing, feedback containing more aspects of socio-emotional information, such as emotionality or communicative meaning, may provide a more explicit external evaluative signal that prompts action. This added evaluative component could facilitate the translation of feedback into adaptive behavioral adjustments in older adults.

From a conceptual perspective, this differentiation refines current accounts of socio-emotional learning in aging by demonstrating that the effectiveness of socio-emotional feedback depends on the correspondence between feedback characteristics and the specific processing stage they are assumed to support. Adopting this stage-specific perspective may help reconcile previously inconsistent findings in the literature and highlights the importance of carefully characterizing feedback stimuli when investigating learning mechanisms during aging.

To conclude, socio-emotional feedback in older adults does not function as a unitary signal that uniformly enhances all stages of feedback processing. Rather, distinct facets of socio-emotional information appear to differentially support early detection and later evaluative processes. While social relevance may suffice to enhance early outcome detection, emotional and communicative features seem to become increasingly important when feedback must be maintained, updated, and used to guide future behavior.

6.3 Strengths and limitations

The current studies of the present doctoral thesis come with limitations and leave some open questions, which should be addressed. While it could be shown that learning in older adults can be increased by receiving feedback with socio-emotional information, the effects in younger adults seem to be more variable. Study 1 supported the assumption that potential benefits of socio-emotional feedback in younger adults depend on the stage of the learning process and influence only specific learning mechanisms. In particular, socio-emotional feedback affected reaction times, which became faster earlier in easy compared to the difficult learning task. These findings suggest that enhanced working memory load alone is unlikely to represent the main limiting factor. Instead, it appears more plausible that younger adults are more sensitive to subtle differences in feedback stimuli when these are more strictly controlled, as was the case in the easier learning tasks used in Studies 2 and 3.

Creating comparable stimuli was one of the biggest challenges in the preparation of this dissertation (Pfabigan et al., 2019; Shigeto et al., 2011). In Study 2, feedback stimuli were not color-coded, in contrast to Study 1 and Study 3, where intuitive color cues were used to signal feedback valence (green for correct and red for incorrect feedback). The absence of color coding in Study 2 may have increased ambiguity in the weak emotional feedback condition, particularly for older adults even though we understood that due to the pre-study, participants were able to discriminate positive and negative feedback. However, the pre-ratings used in Studies 2 (mean age= 24.39 years (*SD* = 6.73), range = 18–56 years) and 3 (mean age= 33.5 years (*SD* = 10.1, range = 18–66 years) were predominantly obtained from younger adults and did not sufficiently include older adults of the age groups we recruited for the main experiments. Thus, age-related differences may not have fully captured the perceptual and emotional relevance for older adults in the feedback

stimuli. Age-related changes in emotion perception could have made it more difficult for older participants to reliably categorize the valence of subtly expressed facial feedback, thereby potentially inflating differences between weak and strong emotional feedback conditions in accuracy (Ruffman et al., 2008; Slessor et al., 2022; Sullivan & Ruffman, 2004). While this design choice allowed a more naturalistic presentation of emotional expressions, it also reduced congruency across studies and used feedback stimuli and may have introduced additional perceptual demands. In hindsight, ensuring consistent valence signaling across all studies, for example through the use of color stimuli in all feedback conditions, might have strengthened the interpretability of the behavioral and neural processing effects and increased comparability between feedback types. At the same time, the fact that robust learning benefits were still observed in older adults despite this ambiguity further highlights the reinforcing value of socio-emotional information in this age group.

Another methodological limitation concerns the between-subjects design employed across the studies. This design choice was driven by the large number of trials required for reliable ERP analyses and the aim to avoid fatigue and learning transfer effects that would likely occur in within-subject designs. While this approach ensured sufficient statistical power for ERP analyses, it also limited the extent to which intraindividual differences in feedback processing across conditions and linked to behavioral performance could be examined (Luck & Kappenmann, 2012; Raz & Lindenberger, 2011). Future studies using within-subject or mixed designs could provide a more detailed assessment of how individual learners flexibly adapt to different feedback characteristics. Also, to examine whether the found effects are truly aging effects and change over time, longitudinal studies or re-assessments could be beneficial.

Another limitation of the present thesis is the missing diversity in older adults, which reduce the possibility to generalize obtained results. Diversity in this case means that our sample size in older adults primarily included groups with a higher educational status, possibly influencing learning processes and compensatory mechanisms (Reuter-Lorenz & Park, 2014). In addition, there is evidence that lifestyle factors such as social participation, nutrition and physical exercise influence cognitive aging and thus may influence learning from feedback as well (Morr et al., 2022; Reuter-Lorenz & Park, 2014). These factors may moderate the benefit from socio-emotional feedback or give even more insights about which characteristics benefit whom. Again, due to the needed power and through linking this to ERP studies, which would have tremendously increased the necessary sample size, we focused on the neural mechanisms without additional correlational analyses (Luck & Kappenmann, 2012). For instance, social participation, especially in aging, is assumed to influence cognitive abilities and therefore also could influence the ability to learn from socio-emotional feedback (Bourassa et al., 2017). Additionally, older adults in our sample were likely highly motivated, as they proactively chose to participate in our studies. Further, the sample was socially and physically active. A more diverse sample might have strengthened our effects and would have allowed us to examine which subgroups of older adults benefit from socio-emotional feedback during learning, thereby identifying which lifestyle factors may contribute to additional compensatory learning mechanisms in aging.

6.4 Outlook

As mentioned above, one of the strengths of the present work was taking a first step towards successfully separating socio-emotional feedback into its facets: emotionality, sociality, and communicative meaning and thereby enhancing our understanding of which facets lead to specific learning and processing benefits especially in older adults. The present work began by

disentangling different facets of socio-emotional feedback. It showed that socio-emotional feedback in the form of facial expressions, but also unfamiliar social feedback such as hand gestures, led to both learning benefits and processing advantages in older adults, whereas findings on younger adults were more variable. However, the influence of communicative meaning was not directly investigated in either younger or older adults. Building on this approach, future research should explicitly examine feedback with communicative meaning in the absence of emotional or social information to determine whether such feedback yields comparable learning benefits or is processed differently. This could possibly be achieved through creating communicative signals with abstract shapes. Employing these carefully matched, comparably complex feedback stimuli with and without communicative meaning and either social or emotional information will be critical for identifying potential age-related differences and their underlying neural substrates in learning from feedback.

A further open question concerns which individual difference factors predict whether older adults benefit from socio-emotional feedback-induced learning. Given the above-mentioned limitations and focus of the present thesis, it remains unclear whether the observed benefits generalize across older adults or are primarily evident in individuals with specific lifestyle characteristics. In particular, levels of social participation, physical activity, and health-related behaviors may serve as key predictors or moderators of the extent to which socio-emotional information acts as a compensator for learning in later life, independently of socioeconomic status (Bourassa et al., 2017; Hedden & Gabrieli, 2004; Morr et al., 2022). Future studies should therefore operationalize these health-related concepts, thereby enabling comparisons between low and high levels of these lifestyle factors and their impact on learning from socio-emotional feedback.

Initial correlational evidence for this predictive relationship was obtained in an ongoing study including N = 82 older adults. Using the easy version of the probabilistic learning task employed throughout this dissertation, socio-emotional feedback in the form of facial expressions was contrasted with non-emotional feedback (scrambled faces, analogously to Study 1). In addition, we used self-report measures for physical exercise, social participation, nutrition and their perceived importance, as well as the execution for the past four weeks and the past 10 years. Learning performance was indicated by accuracy and reaction times. Again, we showed that also with the feedback stimuli used in Study 1 (scrambled vs. non-scrambled faces, intuitively colored), older adults learned more accurately after socio-emotional than non-emotional feedback. In a further analysis, findings revealed that general learning performance was predicted by age and fluid intelligence. Conducting a hierarchical regression after controlling for age and fluid intelligence did not lead to additional significant effects of lifestyle factors on learning through socio-emotional feedback. However, these results should be considered preliminary, as the current analyses are limited by insufficient statistical power.

Beyond cross-sectional comparisons, a particularly promising direction for future research lies in longitudinal approaches. While the present dissertation provides insights into age-related differences in socio-emotional feedback processing, it cannot address how these differences evolve and change within individuals across the adult lifespan. Longitudinal designs would allow the investigation of intraindividual paths in the use of socio-emotional feedback and their relation to motivational shifts, as proposed by lifespan theories such as the SST (Carstensen, 1991). These longitudinal approaches could clarify whether the observed benefits of socio-emotional feedback in older adults reflect stable age group differences or dynamic adaptations that unfold gradually with aging and lifestyle. This is particularly interesting, because lifestyle factors have been shown

to influence trajectories of cognitive aging and may affect neural systems that are particularly susceptible to age-related decline, such as the dopaminergic system (Bourassa et al., 2017; Hedden & Gabrieli, 2004). Given that changes in dopaminergic functioning are observable in neurodegenerative processes, including preclinical Alzheimer's disease (Hedden & Gabrieli, 2004; Zhang et al., 2025) and parkinson´s disease (Collier et al., 2011; Harsing, 2008), feedback-induced learning may represent a sensitive domain in which subtle cognitive changes become apparent (Kamp et al., 2024; Legaz et al., 2022). At the same time, processing of affective stimuli appears to remain relatively stable across older adults, as has been shown in the present work. This preservation may indicate that socio-emotional feedback has the potential to partially compensate for learning reductions associated also with early cognitive impairment.

Finally, intervention studies examining learning trajectories over time while controlling for lifestyle and health-related factors would provide valuable insights into whether socio-emotional feedback can be used to enhance learning in older adults.

Overall, the present work suggests that socio-emotional feedback may represent a preserved and potentially compensatory mechanism supporting learning in older adults. Future research integrating experimental, longitudinal, and intervention approaches would be essential to clarify its mechanisms and practical applications for promoting cognitive health in aging.

6.5 Practical implications

The findings of the present thesis provide important implications for the practical design of learning environments across the lifespan, particularly with respect to how feedback is conveyed in digital, or educational contexts. Social and emotional information in feedback revealed to be a powerful behavioral learning supporter in aging. Importantly, these behavioral benefits were

accompanied by changes in early feedback detection and the updating of task-relevant information in working memory, indicating that socio-emotional feedback does not merely increase motivation and indirectly supports learning-related neural processes. These results highlight the potential of feedback design as a low-cost and scalable intervention to support learning and cognitive engagement in aging populations.

One central implication of the present findings therefore concerns the design of digital cognitive training tools and applications for older adults. Embedding socio-emotional elements into feedback, such as socially or emotionally expressive signals, may increase the motivational and biologically determined relevance of learning outcomes and thereby support sustained engagement with training programs. This is particularly interesting given that the long-term use of digital cognitive interventions for older adults remains a major challenge, although such interventions may be effective in maintaining or even improving cognitive health (Ballesteros et al., 2015; Bonnechère et al., 2020). By increasing the subjective relevance of feedback, socio-emotional design elements may not only enhance learning performance but also promote continued participation over time.

Beyond digital cognitive training, the present findings may also have implications for broader educational and occupational learning environments. In aging societies, lifelong learning is increasingly important for maintaining employability and supporting active participation in social and professional contexts. Feedback systems that incorporate socio-emotional information may therefore help attenuate age-related differences in learning performance and may support the acquisition of new skills in older adults.

Overall, the present findings highlight the potential of socio-emotional feedback to support learning and engagement in older adults. At the same time, they suggest that feedback design should consider the cognitive demands of the learning situation and the processing characteristics of different age groups.

7 Final conclusion

This doctoral thesis contributes to a more differentiated understanding of feedback-induced learning across the adult lifespan by demonstrating that age-related differences in learning from socio-emotional feedback are not primarily driven by a general decline in feedback sensitivity. Instead, the findings support the view that learning differences reflect changes in how feedback information is integrated into ongoing cognitive processes, depending on task demands, feedback characteristics, and motivational relevance.

By systematically varying working memory load and key properties of feedback, the present work shows that socio-emotional and social feedback can remain effective across aging. Importantly, this effectiveness is not dependent on socio-emotionality alone, but rather on the accessibility and meaningfulness of feedback information. These results suggest that learning from socio-emotional feedback is shaped by an interplay between cognitive resources and motivational engagement, and that this interplay is different with age without resulting in a loss of learning potential per se.

From a theoretical perspective, the present findings challenge deficit-oriented views of cognitive aging that assume a uniform decline in learning-related mechanisms. Instead, they support models that emphasize functional reorganization and adaptive strategy use in aging. Feedback-induced learning appears to remain flexible and modifiable, assuming that feedback information can be successfully integrated into active cognitive representations. In this sense, aging may be better understood as a shift in processing priorities driven by motivational changes that are biologically constrained but can be partially counterbalanced through compensatory mechanisms.

Beyond their theoretical implications, the present findings contribute to ongoing discussions about active aging and participation in modern societies. By demonstrating that older adults can recruit effective learning strategies under appropriate conditions, the present work emphasizes the potential of thoughtfully designed feedback environments to support learning, motivation, and engagement across the adult lifespan, thereby highlighting the importance of designing learning environments that support cognitive engagement across the adult lifespan.

8 References

Abler, B., & Kessler, H. (2011). *ERQ. Emotion regulation questionnaire - [verfahrensdokumentation aus PSYNDEX tests-nr. 9006192 und fragebogen]. In leibniz-zentrum für psychologische information und dokumentation (ZPID) (hrsg.), elektronisches testarchiv. Trier: ZPID.* https://doi.org/10.23668/psycharchives.402

Abrosoft. (2016). Fantamorph (5.0) [Software]. Abrosoft. http://www.fantamorph.com/

Adolphs, R. (2009). The social brain: Neural basis of social knowledge. *Annual Review of Psychology*, *60*, 693–716. https://doi.org/10.1146/annurev.psych.60.110707.163514

Albrecht, C., & Bellebaum, C. (2021). Effects of trait empathy and expectation on the processing of observed actions. *Cognitive, Affective, & Behavioral Neuroscience*, *21*, 156–171. https://doi.org/10.3758/s13415-020-00857-7

Alexander, G. E., Chen, K., Merkley, T. L., Reiman, E. M., Caselli, R. J., Aschenbrenner, M., Santerre-Lemmon, L., Lewis, D. J., Pietrini, P., Teipel, S. J., Hampel, H., Rapoport, S. I., & Moeller, J. R. (2006). Regional network of magnetic resonance imaging gray matter volume in healthy aging. *NeuroReport*, *17*. https://journals.lww.com/neuroreport/fulltext/2006/07170/regional_network_of_magnetic_resonance_imaging.2.aspx

Alexander, W. H., & Brown, J. W. (2011). Medial prefrontal cortex as an action-outcome predictor. *Nature Neuroscience*, *14*, 1338–1344. https://doi.org/10.1038/nn.2921

Alexander, W. H., & Brown, J. W. (2019). The role of the anterior cingulate cortex in prediction error and signaling surprise. *Topics in Cognitive Science*, *11*, 119–135. https://doi.org/10.1111/tops.12307

Arbel, Y. (2020). The effect of task difficulty on feedback processing in children. *International Journal of Psychophysiology*, *153*, 1–7. https://doi.org/10.1016/j.ijpsycho.2020.04.014

Arbel, Y., & Fox, A. B. (2021). Electrophysiological examination of feedback-based learning in 8–11-year-old children. *Frontiers in Psychology, Volume 12 - 2021*. https://doi.org/10.3389/fpsyg.2021.640270

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*, 179–186. https://doi.org/10.1016/j.neuropsychologia.2017.03.003

Arbel, Y., & Wu, H. (2016). A neurophysiological examination of quality of learning in a feedback-based learning task. *Neuropsychologia*, *93*, 13–20. https://doi.org/10.1016/j.neuropsychologia.2016.10.001

Bäckman, L., & Farde, L. (2005). The role of dopamine systems in cognitive aging. *Cognitive Neuroscience of Aging: Linking Cognitive and Cerebral Aging*. https://doi.org/10.1093/acprof:oso/9780195156744.003.0003

Bäckman, L., Ginovart, N., Dixon, R. A., Wahlin, T. B. R., Wahlin, A., Halldin, C., & Farde, L. (2000). Age-related cognitive deficits mediated by changes in the striatal dopamine system. *AMERICAN JOURNAL OF PSYCHIATRY*, *157*, 635–637. http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-36306

Bäckman, L., Lindenberger, U., Li, S.-C., & Nyberg, L. (2010). Linking cognitive aging to alterations in dopamine neurotransmitter functioning: Recent data and future avenues. *Neuroscience & Biobehavioral Reviews*, *34*, 670–677. https://doi.org/10.1016/j.neubiorev.2009.12.008

Bäckman, L., Nyberg, L., Lindenberger, U., Li, S.-C., & Farde, L. (2006). The correlative triad among aging, dopamine, and cognition: Current status and future prospects. *Neuroscience & Biobehavioral Reviews*, *30*, 791–807. https://doi.org/10.1016/j.neubiorev.2006.06.005

Ballesteros, S., Mayas, J., Prieto, A., Toril, P., Pita, C., León Laura, P. de, Reales, J. M., & Waterworth, J. A. (2015). A randomized controlled trial of brain training with non-action video games in older adults: Results of the 3-month follow-up. *Frontiers in Aging*

Neuroscience, Volume 7 - 2015. https://www.frontiersin.org/journals/aging-neuroscience/articles/10.3389/fnagi.2015.00045

Baltes, P., & Lindenberger, U. (1999). Lifespan psychology: Theory and application to intellectual functioning. *Annual Review of Psychology, 50*, 471–507. https://doi.org/10.1146/annurev.psych.50.1.471

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

Bellebaum, C., Kobza, S., Thiele, S., & Daum, I. (2011). Processing of expected and unexpected monetary performance outcomes in healthy older subjects. *Behavioral Neuroscience, 125*, 241–251. https://doi.org/10.1037/a0022536

Berg, B. van den, Geib, B. R., Martín, R. S., & Woldorff, M. G. (2019). A key role for stimulus-specific updating of the sensory cortices in the learning of stimulus–reward associations. *Social Cognitive and Affective Neuroscience, 14*, 173–187. https://doi.org/10.1093/scan/nsy116

Bethlehem, R. A. I., Seidlitz, J., White, S. R., Vogel, J. W., Anderson, K. M., Adamson, C., Adler, S., Alexopoulos, G. S., Anagnostou, E., Areces-Gonzalez, A., Astle, D. E., Auyeung, B., Ayub, M., Bae, J., Ball, G., Baron-Cohen, S., Beare, R., Bedford, S. A., Benegal, V., … VETSA. (2022). Brain charts for the human lifespan. *Nature, 604*, 525–533. https://doi.org/10.1038/s41586-022-04554-y

Boksem, M. A. S., Kostermans, E., & Cremer, D. D. (2011a). Failing where others have succeeded: Medial frontal negativity tracks failure in a social context. *Psychophysiology, 48*, 973–979. https://doi.org/10.1111/j.1469-8986.2010.01163.x

Boksem, M. A. S., Ruys, K. I., & Aarts, H. (2011b). Facing disapproval: Performance monitoring in a social context. *Social Neuroscience, 6*, 360–368. https://doi.org/10.1080/17470919.2011.556813

Bonnechère, B., Langley, C., & Sahakian, B. J. (2020). The use of commercial computerised cognitive games in older adults: A meta-analysis. *Scientific Reports*, *10*, 15276. https://doi.org/10.1038/s41598-020-72281-3

Borries, A. K. L. von, Verkes, R. J., Bulten, B. H., Cools, R., & Bruijn, E. R. A. de. (2013). Feedback-related negativity codes outcome valence, but not outcome expectancy, during reversal learning. *Cognitive, Affective, & Behavioral Neuroscience*, *13*, 737–746. https://doi.org/10.3758/s13415-013-0150-1

Boudewyn, M. A., Luck, S. J., Farrens, J. L., & Kappenman, E. S. (2018). How many trials does it take to get a significant ERP effect? It depends. *Psychophysiology*, *55*(6), e13049. https://doi.org/10.1111/psyp.13049

Bourassa, K. J., Memel, M., Woolverton, C., & Sbarra, D. A. (2017). Social participation predicts cognitive functioning in aging adults over time: Comparisons with physical health, depression, and physical activity. *Aging & Mental Health*, *21*, 133–146. https://doi.org/10.1080/13607863.2015.1081152

BrainVision Recorder (Vers. 1.23.0001) [Software]. (2020). Gilching; Germany; Brain Products GmbH.

Braunstein, L. M., Gross, J. J., & Ochsner, K. N. (2017). Explicit and implicit emotion regulation: A multi-level framework. *Social Cognitive and Affective Neuroscience*, *12*, 1545–1557. https://doi.org/10.1093/scan/nsx096

Braunwarth, J. I., & Ferdinand, N. K. (2025). The impact of emotional feedback in learning easy and difficult tasks – an ERP study. *Cognitive, Affective, & Behavioral Neuroscience*. https://doi.org/10.3758/s13415-025-01284-2

Braunwarth, J. I., & Ferdinand, N. K. (2026). *Age differences in socio-emotional feedback processing during learning: An ERP study* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/yxsd5_v2

Braver, T. S., & Barch, D. M. (2002). A theory of cognitive control, aging cognition, and neuromodulation. *Neuroscience & Biobehavioral Reviews*, *26*, 809–817. https://doi.org/10.1016/S0149-7634(02)00067-2

Braver, T. S., Barch, D. M., Gray, J. R., Molfese, D. L., & Snyder, A. (2001). Anterior cingulate cortex and response conflict: Effects of frequency, inhibition and errors. *Cerebral Cortex*, *11*, 825–836. https://doi.org/10.1093/cercor/11.9.825

Brose, A., Scheibe, S., & Schmiedek, F. (2013). Life contexts make a difference: Emotional stability in younger and older adults. *Psychology and Aging*, *28*, 148–159. https://doi.org/10.1037/a0030047

Brown, J. W., & Alexander, W. H. (2017). Foraging value, risk avoidance, and multiple control signals: How the anterior cingulate cortex controls value-based decision-making. *Journal of Cognitive Neuroscience*, *29*, 1656–1673. https://doi.org/10.1162/jocn_a_01140

Cabeza, R., Anderson, N. D., Locantore, J. K., & McIntosh, A. R. (2002). Aging gracefully: Compensatory brain activity in high-performing older adults. *NeuroImage*, *17*, 1394–1402. https://doi.org/10.1006/nimg.2002.1280

Carstensen, L. L. (1991). Selectivity theory: Social activity in life-span context. *Annual Review of Gerontology and Geriatrics*, *11*, 195–217.

Carstensen, L. L. (2021). Socioemotional selectivity theory: The role of perceived endings in human motivation. *The Gerontologist*, *61*, 1188–1196. https://doi.org/10.1093/geront/gnab116

Carstensen, L. L., Mikels, J. A., & Mather, M. (2006). Fifteen - aging and the intersection of cognition, motivation, and emotion. In J. E. Birren, K. W. Schaie, R. P. Abeles, M. Gatz, & T. A. Salthouse (Eds.), *Handbook of the Psychology of Aging (Sixth Edition)* (pp. 343–362). Academic Press. https://doi.org/https://doi.org/10.1016/B978-012101264-9/50018-5

Carstensen, L., Isaacowitz, D., & Charles, S. (1999). Taking time seriously: A theory of socioemotional selectivity. *The American Psychologist*, *54*, 165–181. https://doi.org/10.1037//0003-066X.54.3.165

Carstensen, L., Pasupathi, M., Mayr, U., & Nesselroade, J. (2000). Emotional experience in everyday life across the adult life span. *Journal of Personality and Social Psychology*, *79*, 644–655. https://doi.org/10.1037//0022-3514.79.4.644

Carstensen, L., Turan, B., Scheibe, S., Ram, N., Hershfield, H., Samanez-Larkin, G., Brooks, K., & Nesselroade, J. (2010). Emotional experience improves with age: Evidence based on over 10 years of experience sampling. *Psychology and Aging*, *26*, 21–33. https://doi.org/10.1037/a0021285

Charles, S. T. (2010). Strength and vulnerability integration: A model of emotional well-being across adulthood. *Psychological Bulletin*, *136*, 1068–1091. https://doi.org/10.1037/a0021232

Charles, S. T., & Luong, G. (2013). Emotional experience across adulthood: The theoretical model of strength and vulnerability integration. *Current Directions in Psychological Science*, *22*, 443–448. https://doi.org/10.1177/0963721413497013

Charles, S. T., & Piazza, J. R. (2024). Looking back, forging ahead: Fifteen years of strength and vulnerability integration (SAVI). *Current Opinion in Psychology*, *55*, 101751. https://doi.org/10.1016/j.copsyc.2023.101751

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587

Cohen, M. X. (2008). Neurocomputational mechanisms of reinforcement-guided learning in humans: A review. *Cognitive, Affective, & Behavioral Neuroscience*, *8*, 113–125. https://doi.org/10.3758/CABN.8.2.113

Cohen, M. X., & Ranganath, C. (2007). Reinforcement learning signals predict future decisions. *The Journal of Neuroscience*, *27*, 371. https://doi.org/10.1523/JNEUROSCI.4421-06.2007

Coles, N., Larsen, J., & Lench, H. (2019). A meta-analysis of the facial feedback literature: Effects of facial feedback on emotional experience are small and variable. *Psychological Bulletin*, *145*, 610–651. https://doi.org/10.1037/bul0000194

Collier, T. J., Kanaan, N. M., & Kordower, J. H. (2011). Ageing as a primary risk factor for parkinson's disease: Evidence from studies of non-human primates. *Nature Reviews Neuroscience*, *12*, 359–366. https://doi.org/10.1038/nrn3039

Collins, A. G. E., & Frank, M. J. (2012). How much of reinforcement learning is working memory, not reinforcement learning? A behavioral, computational, and neurogenetic analysis. *The European Journal of Neuroscience*, *35*, 1024–1035. https://doi.org/10.1111/j.1460-9568.2011.07980.x

Conroy, M. A., & Polich, J. (2007). Normative variation of P3a and P3b from a large sample. *Journal of Psychophysiology*, *21*, 22–32. https://doi.org/10.1027/0269-8803.21.1.22

Daffner, K. R., Chong, H., Sun, X., Tarbi, E. C., Riis, J. L., McGinnis, S. M., & Holcomb, P. J. (2011). Mechanisms underlying age- and performance-related differences in working memory. *Journal of Cognitive Neuroscience*, *23*, 1298–1314. https://doi.org/10.1162/jocn.2010.21540

Davis, S. W., Dennis, N. A., Daselaar, S. M., Fleck, M. S., & Cabeza, R. (2008). Qué PASA? The posterior–anterior shift in aging. *Cerebral Cortex*, *18*, 1201–1209. https://doi.org/10.1093/cercor/bhm155

Debener, S., Makeig, S., Delorme, A., & Engel, A. K. (2005). What is novel in the novelty oddball paradigm? Functional significance of the novelty P3 event-related potential as revealed by independent component analysis. *Cognitive Brain Research*, *22*, 309–321. https://doi.org/10.1016/j.cogbrainres.2004.09.006

DeBruine, L. M. (2018). debruine/webmorph: Beta release 2 (Version v0.0.0.9001). Zenodo. https://doi.org/10.5281/zenodo.1162670.

Dekkers, L. M. S., Molen, M. J. W. van der, Moor, B. G., Veen, F. M. van der, & Molen, M. W. van der. (2015). Cardiac and electro-cortical concomitants of social feedback processing in women. *Social Cognitive and Affective Neuroscience*, *10*, 1506–1514. https://doi.org/10.1093/scan/nsv039

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*, 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Dempster, F. N. (1992). The rise and fall of the inhibitory mechanism: Toward a unified theory of cognitive development and aging. *Developmental Review*, *12*, 45–75. https://doi.org/10.1016/0273-2297(92)90003-K

Densley, K., Davidson, S., & Gunn, J. M. (2013). Evaluation of the social participation questionnaire in adult patients with depressive symptoms using rasch analysis. *Quality of Life Research*, *22*, 1987–1997. https://doi.org/10.1007/s11136-013-0354-4

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being. *Psychological Bulletin*, *125*, 276–302. https://doi.org/10.1037/0033-2909.125.2.276

Donchin, E., & Coles, M. (1988). Is the P300 component a manifestation of context updating? *Behavioral and Brain Sciences - BEHAV BRAIN SCI*, *11*, 357–427. https://doi.org/10.1017/S0140525X00058027

Ebner, N. C., Riediger, M., & Lindenberger, U. (2010). FACES–a database of facial expressions in young, middle-aged, and older women and men: Development and validation. *Behavior Research Methods*, *42*, 351–362. https://doi.org/10.3758/BRM.42.1.351

Ehinger, B. V., & Dimigen, O. (2019). Unfold: an integrated toolbox for overlap correction, non-linear modeling, and regression-based EEG analysis. *PeerJ*, 7, e7838. https://doi.org/10.7717/peerj.7838

Eppinger, B., Hämmerer, D., & Li, S.-C. (2011). Neuromodulation of reward-based learning and decision making in human aging. *Annals of the New York Academy of Sciences*, *1235*, 1–17. https://doi.org/10.1111/j.1749-6632.2011.06230.x

Eppinger, B., Kray, J., Mock, B., & Mecklinger, A. (2008). Better or worse than expected? Aging, learning, and the ERN. *Neuropsychologia*, *46*, 521–539. https://doi.org/10.1016/j.neuropsychologia.2007.09.001

Eppinger, B., Mock, B., & Kray, J. (2009). Developmental differences in learning and error processing: Evidence from ERPs. *Psychophysiology*, *46*, 1043–1053. https://doi.org/10.1111/j.1469-8986.2009.00838.x

Eyler, L. T., Sherzai, A., Kaup, A. R., & Jeste, D. V. (2011). A review of functional brain imaging correlates of successful cognitive aging. *Biological Psychiatry*, *70*, 115–122. https://doi.org/10.1016/j.biopsych.2010.12.032

Falkenstein, M., Hohnsbein, J., Hoormann, J., Blanke, L., Brunia, C. H. M., Gaillard, A. W. K., & Kok, A. (1990). Effects of errors in choice reaction tasks on the ERP under focused and divided attention. In *Psychophysiological brain research* (pp. 192–195). Tilburg University Press.

Farokhian, F., Yang, C., Beheshti, I., Matsuda, H., & Wu, S. (2017). Age-related gray and white matter changes in normal adult brains. *Aging and Disease*, *8*, 899–909. https://doi.org/10.14336/AD.2017.0502

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175–191. https://doi.org/10.3758/BF03193146

Ferdinand, N. K. (2019). The influence of task complexity and information value on feedback processing in younger and older adults: No evidence for a positivity bias during feedback-induced learning in older adults. *Brain Research*, *1717*, 74–85. https://doi.org/10.1016/j.brainres.2019.04.011

Ferdinand, N. K., & Czernochowski, D. (2018). Motivational influences on performance monitoring and cognitive control across the adult lifespan. *Frontiers in Psychology*, *9*, 1018. https://doi.org/10.3389/fpsyg.2018.01018

Ferdinand, N. K., & Hilz, M. (2020). Emotional feedback ameliorates older adults' feedback-induced learning. *PLoS ONE*, *15*, 1–20. https://doi.org/10.1371/journal.pone.0231964

Ferdinand, N. K., & Kray, J. (2013). Age-related changes in processing positive and negative feedback: Is there a positivity effect for older adults? *Biological Psychology*, *94*, 235–241. https://doi.org/10.1016/j.biopsycho.2013.07.006

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*, 12087–12092. https://doi.org/10.1523/JNEUROSCI.1410-12.2012

Ferdinand, N. K., & Opitz, B. (2014). Different aspects of performance feedback engage different brain areas: Disentangling valence and expectancy in feedback processing. *Scientific Reports*, *4*, 1–8. https://doi.org/10.1038/srep05986

Ferdinand, N. K., Paulus, M., Schuwerk, T., & Kühn-Popp, N. (2018). Editorial: Social and emotional influences on human development: Perspectives from developmental neuroscience. *Frontiers in Psychology, Volume 9 - 2018*. https://doi.org/10.3389/fpsyg.2018.02490

Fernandes, C., Pasion, R., Gonçalves, A. R., Ferreira-Santos, F., Barbosa, F., Martins, I. P., & Marques-Teixeira, J. (2018). Age differences in neural correlates of feedback processing after economic decisions under risk. *Neurobiology of Aging*, *65*, 51–59. https://doi.org/10.1016/j.neurobiolaging.2018.01.003

Fischer, A. G., & Ullsperger, M. (2013). Real and fictive outcomes are processed differently but converge on a common adaptive mechanism. *Neuron*, *79*, 1243–1255. https://doi.org/10.1016/j.neuron.2013.07.006

Fjell, A. M., McEvoy, L., Holland, D., Dale, A. M., & Walhovd, K. B. (2014). What is normal in normal aging? Effects of aging, amyloid and alzheimer's disease on the cerebral cortex and the hippocampus. *Progress in Neurobiology*, *117*, 20–40. https://doi.org/10.1016/j.pneurobio.2014.02.004

Fjell, A., & Walhovd, K. (2010). Structural brain changes in aging: Courses, causes and cognitive consequences. *Reviews in the Neurosciences*, *21*, 187–221. https://doi.org/10.1515/REVNEURO.2010.21.3.187

Flores, A., Münte, T. F., & Doñamayor, N. (2015). Event-related EEG responses to anticipation and delivery of monetary and social reward. *Biological Psychology*, *109*, 10–19. https://doi.org/10.1016/j.biopsycho.2015.04.005

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). "Mini-mental state": A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research*, *12*, 189–198.

Frank, M. J., Woroch, B. S., & Curran, T. (2005). Error-related negativity predicts reinforcement learning and conflict biases. *Neuron*, *47*, 495–501. https://doi.org/10.1016/j.neuron.2005.06.020

Friedman, D., Kazmerski, V., & Fabiani, M. (1997). An overview of age-related changes in the scalp distribution of P3b. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, *104*, 498–513. https://doi.org/10.1016/S0168-5597(97)00036-1

Friedman, D., Nessler, D., Jr, R. J., Ritter, W., & Bersick, M. (2007). Age-related changes in executive function: An event-related potential (ERP) investigation of task-switching. *Aging, Neuropsychology, and Cognition*, *15*, 95–128. https://doi.org/10.1080/13825580701533769

Fu, Y. (2005). Measuring personal networks with daily contacts: A single-item survey question and the contact diary. *Social Networks*, *27*, 169–186. https://doi.org/10.1016/j.socnet.2005.01.008

Gaál, Z. A., & Czigler, I. (2015). Age-related processing strategies and go–nogo effects in task-switching: An ERP study. *Frontiers in Human Neuroscience, Volume 9 - 2015*. https://www.frontiersin.org/journals/human-neuroscience/articles/10.3389/fnhum.2015.00177

Gajewski, P. D., Ferdinand, N. K., Kray, J., & Falkenstein, M. (2018). Understanding sources of adult age differences in task switching: Evidence from behavioral and ERP studies. *Neuroscience & Biobehavioral Reviews*, *92*, 255–275. https://doi.org/10.1016/j.neubiorev.2018.05.029

Gajewski, P., & Falkenstein, M. (2014). Age-related effects on ERP and oscillatory EEG-dynamics in a 2-back task. *Journal of Psychophysiology*, *28*, 162–177. https://doi.org/10.1027/0269-8803/a000123

Geen, R. G., & Gange, J. J. (1977). Drive theory of social facilitation: Twelve years of theory and research. *Psychological Bulletin*, *84*, 1267.

Gehring, W. J., Goss, B., Coles, M. G. H., Meyer, D. E., & Donchin, E. (1993). A neural system for error detection and compensation. *Psychological Science*, *4*, 385–390. https://doi.org/10.1111/j.1467-9280.1993.tb00586.x

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

Gheza, D., Paul, K., & Pourtois, G. (2018). Dissociable effects of reward and expectancy during evaluative feedback processing revealed by topographic ERP mapping analysis. *International Journal of Psychophysiology*, *132*, 213–225. https://doi.org/10.1016/j.ijpsycho.2017.11.013

Giorgio, A., Santelli, L., Tomassini, V., Bosnell, R., Smith, S., Stefano, N. D., & Johansen-Berg, H. (2010). Age-related changes in grey and white matter structure throughout adulthood. *NeuroImage*, *51*, 943–951. https://doi.org/10.1016/j.neuroimage.2010.03.004

Gorlick, M. A., Giguère, G., Glass, B. D., Nix, B. N., Mather, M., & Maddox, W. T. (2013). Attenuating age-related learning deficits: Emotional valenced feedback interacts with task complexity. *Emotion (Washington, D.C.)*, *13*, 250–261. https://doi.org/10.1037/a0030071

Gorlick, M. A., & Maddox, W. T. (2015). Social incentives improve deliberative but not procedural learning in older adults. *Frontiers in Psychology*, *Volume 6 - 2015*. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2015.00430

Grieve, S. M., Clark, C. R., Williams, L. M., Peduto, A. J., & Gordon, E. (2005). Preservation of limbic and paralimbic structures in aging. *Human Brain Mapping*, *25*, 391–401. https://doi.org/10.1002/hbm.20115

Groh, J., & Simons, M. (2025). White matter aging and its impact on brain function. *Neuron*, *113*, 127–139. https://doi.org/10.1016/j.neuron.2024.10.019

Gross, J., Carstensen, L., Pasupathi, M., Tsai, J., Skorpen, C., & Hsu, A. (1997). Emotion and aging: Experience, expression, and control. *Psychology and Aging*, *12*, 590–599. https://doi.org/10.1037/0882-7974.12.4.590

Growney, C. M., & English, T. (2023). Age and cognitive ability predict emotion regulation strategy use. *The Journals of Gerontology: Series B*, *78*, 987–997. https://doi.org/10.1093/geronb/gbad021

Guerrero, L., Bouazzaoui, B., Isingrini, M., & Angel, L. (2022). Involvement of executive control in neural capacity related to working memory in aging: An ERP P300 study. *Cognitive, Affective, & Behavioral Neuroscience*, *22*, 1311–1333. https://doi.org/10.3758/s13415-022-01018-8

Haber, S. (2016). Corticostriatal circuitry. *Dialogues in Clinical Neuroscience*, *18*, 7–21. https://doi.org/10.1007/978-1-4614-6434-1_135-1

Hämmerer, D., Li, S.-C., Müller, V., & Lindenberger, U. (2011). Life span differences in electrophysiological correlates of monitoring gains and losses during probabilistic reinforcement learning. *Journal of Cognitive Neuroscience*, *23*, 579–592. https://doi.org/10.1162/jocn.2010.21475

Handy, T.C. (2005). Event-related potentials: A methods handbook. MIT Press.

Harsing, L. G. (2008). Dopamine and the dopaminergic systems of the brain. In A. Lajtha & E. S. Vizi (Eds.), *Handbook of neurochemistry and molecular neurobiology: Neurotransmitter systems* (pp. 149–170). Springer US. https://doi.org/10.1007/978-0-387-30382-6_7

Hauser, T. U., Iannaccone, R., Stämpfli, P., Drechsler, R., Brandeis, D., Walitza, S., & Brem, S. (2014). The feedback-related negativity (FRN) revisited: New insights into the localization, meaning and network organization. *NeuroImage*, *84*, 159–168. https://doi.org/10.1016/j.neuroimage.2013.08.028

Hedden, T., & Gabrieli, J. D. E. (2004). Insights into the ageing mind: A view from cognitive neuroscience. *Nature Reviews Neuroscience*, *5*, 87–96. https://doi.org/10.1038/nrn1323

Herbert, M., Eppinger, B., & Kray, J. (2011). Younger but not older adults benefit from salient feedback during learning. *Frontiers in Psychology*, *2*. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2011.00171

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*, 679–709. https://doi.org/10.1037/0033-295X.109.4.679

Holroyd, C. B., Hajcak, G., & Larsen, J. T. (2006). The good, the bad and the neutral: Electrophysiological responses to feedback stimuli. *Brain Research*, *1105*, 93–101. https://doi.org/10.1016/j.brainres.2005.12.015

Holroyd, C. B., & Krigolson, O. E. (2007). Reward prediction error signals associated with a modified time estimation task. *Psychophysiology*, *44*, 913–917. https://doi.org/10.1111/j.1469-8986.2007.00561.x

Holroyd, C. B., Pakzad-Vaezi, K. L., & Krigolson, O. E. (2008a). The feedback correct-related positivity: Sensitivity of the event-related brain potential to unexpected positive feedback. *Psychophysiology*, *45*, 688–697. https://doi.org/https://doi.org/10.1111/j.1469-8986.2008.00668.x

Holroyd, C. B., Pakzad-Vaezi, K. L., & Krigolson, O. E. (2008b). The feedback correct-related positivity: Sensitivity of the event-related brain potential to unexpected positive feedback. *Psychophysiology*, *45*, 688–697. https://doi.org/10.1111/j.1469-8986.2008.00668.x

Hurlemann, R., Patin, A., Onur, O. A., Cohen, M. X., Baumgartner, T., Metzler, S., Dziobek, I., Gallinat, J., Wagner, M., Maier, W., & Kendrick, K. M. (2010). Oxytocin enhances amygdala-dependent, socially reinforced learning and emotional empathy in humans. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *30*, 4999–5007. https://doi.org/10.1523/JNEUROSCI.5538-09.2010

Isaacowitz, D. M., & Wolfe, H. E. (2024). Emotion regulation tactics: A key to understanding age (and other between- and within-person) differences in emotion regulation preference and effectiveness. *Emotion Review*, *16*, 252–264. https://doi.org/10.1177/17540739241259567

Itier, R. J., & Taylor, M. J. (2004). N170 or N1? Spatiotemporal differences between object and face processing using ERPs. *Cerebral cortex (New York, N.Y. : 1991)*, *14*(2), 132–142. https://doi.org/10.1093/cercor/bhg111

Jaeger, J. (2018). Digit symbol substitution test: The case for sensitivity over specificity in neuropsychological testing. *Journal of Clinical Psychopharmacology*, *38*, 513–519. https://doi.org/10.1097/JCP.0000000000000941

Jasper, H. H. (1958). Report of the committee on methods of clinical examination in electroencephalography: 1957. *Electroencephalography and Clinical Neurophysiology*, *10*, 370–375. https://doi.org/10.1016/0013-4694(58)90053-1

Kamp, S.-M., Endemann, R., Knopf, L., & Ferdinand, N. K. (2024). Subjective cognitive decline in healthy older adults is associated with altered processing of negative versus positive feedback in a probabilistic learning task. *Frontiers in Psychology*, *15*. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2024.1404345

Kardos, Z., Tóth, B., Boha, R., File, B., & Molnár, M. (2017). Age-dependent characteristics of feedback evaluation related to monetary gains and losses. *International Journal of Psychophysiology*, *122*, 42–49. https://doi.org/10.1016/j.ijpsycho.2016.05.007

Karrer, T. M., Josef, A. K., Mata, R., Morris, E. D., & Samanez-Larkin, G. R. (2017). Reduced dopamine receptors and transporters but not synthesis capacity in normal aging adults: A meta-analysis. *Neurobiology of Aging*, *57*, 36–46. https://doi.org/10.1016/j.neurobiolaging.2017.05.006

Katolikova, N., & Gainetdinov, R. R. (2021). Dopamine system. In S. Offermanns & W. Rosenthal (Eds.), *Encyclopedia of molecular pharmacology* (pp. 554–560). Springer International Publishing. https://doi.org/10.1007/978-3-030-57401-7_51

Kehoe, E. G., Toomey, J. M., Balsters, J. H., & Bokde, A. L. W. (2013). Healthy aging is associated with increased neural processing of positive valence but attenuated processing of emotional arousal: An fMRI study. *Neurobiology of Aging*, *34*, 809–821. https://doi.org/10.1016/j.neurobiolaging.2012.07.006

Kennedy, K., & Raz, N. (2015). Normal aging of the brain. In *Brain mapping: An encyclopedic reference* (Vol. 3, pp. 603–617). https://doi.org/10.1016/B978-0-12-397025-1.00068-3

Kensinger, E. A., & Gutchess, A. H. (2017). Cognitive aging in a social and affective context: Advances over the past 50 years. *The Journals of Gerontology: Series B*, *72*, 61–70. https://doi.org/10.1093/geronb/gbw056

Kirino, E., Belger, A., Goldman-Rakic, P., & McCarthy, G. (2000). Prefrontal activation evoked by infrequent target and novel stimuli in a visual target detection task: An event-related functional magnetic resonance imaging study. *The Journal of Neuroscience*, *20*, 6612. https://doi.org/10.1523/JNEUROSCI.20-17-06612.2000

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

Kirschner, P. A. (2002). Cognitive load theory: Implications of cognitive load theory on the design of learning. *Learning and Instruction*, *12*, 1–10. https://doi.org/10.1016/S0959-4752(01)00014-7

Koban, L., & Pourtois, G. (2014). Brain systems underlying the affective and social monitoring of actions: An integrative review. *Neuroscience & Biobehavioral Reviews*, *46*, 71–84. https://doi.org/10.1016/j.neubiorev.2014.02.014

Koban, L., Pourtois, G., Bediou, B., & Vuilleumier, P. (2012). Effects of social context and predictive relevance on action outcome monitoring. *Cognitive, Affective, & Behavioral Neuroscience*, *12*, 460–478. https://doi.org/10.3758/s13415-012-0091-0

Kok, A. (2001). On the utility of P3 amplitude as a measure of processing capacity. *Psychophysiology*, *38*, 557–577. https://doi.org/DOI: 10.1017/S0048577201990559

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., Hassall, C. D., Satel, J., & Klein, R. M. (2015). The impact of cognitive load on reward evaluation. *Brain Research*, *1627*, 225–232. https://doi.org/10.1016/j.brainres.2015.09.028

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

Kujawa, A., Arfer, K. B., Klein, D. N., & Proudfit, G. H. (2014). Electrocortical reactivity to social feedback in youth: A pilot study of the island getaway task. *Developmental Cognitive Neuroscience*, *10*, 140–147. https://doi.org/10.1016/j.dcn.2014.08.008

Leclerc, C. M., & Kensinger, E. A. (2008). Effects of age on detection of emotional information. *Psychology and Aging*, *23*, 209–2015. https://doi.org/10.1037/0882-7974.23.1.209

Lee, E., Kang, J. I., Park, I. H., Kim, J.-J., & An, S. K. (2008). Is a neutral face really evaluated as being emotionally neutral? *Psychiatry Research*, *157*, 77–85. https://doi.org/10.1016/j.psychres.2007.02.005

Lee, J., & Kim, H.-J. (2022). Normal aging induces changes in the brain and neurodegeneration progress: Review of the structural, biochemical, metabolic, cellular, and molecular changes. *Frontiers in Aging Neuroscience, Volume 14 - 2022*. https://www.frontiersin.org/journals/aging-neuroscience/articles/10.3389/fnagi.2022.931536

Legaz, A., Abrevaya, S., Dottori, M., Campo, C. G., Birba, A., Caro, M. M., Aguirre, J., Slachevsky, A., Aranguiz, R., Serrano, C., Gillan, C. M., Leroi, I., García, A. M., Fittipaldi, S., & Ibañez, A. (2022). Multimodal mechanisms of human socially reinforced learning across neurodegenerative diseases. *Brain*, *145*, 1052–1068. https://doi.org/10.1093/brain/awab345

Lehrl, S. (2005). *Mehrfachwahl-wortschatz-intelligenztest : MWT-b* (5., unverä). Spitta.

Lemaître, H., Goldman, A., Sambataro, F., Verchinski, B., Meyer-Lindenberg, A., Weinberger, D., & Mattay, V. (2012). Normal age-related brain morphometric changes: Nonuniformity across cortical thickness, surface area and gray matter volume? *Neurobiology of Aging*, *33*, 617.e1–9. https://doi.org/10.1016/j.neurobiolaging.2010.07.013

Leue, A., Nieden, K., Scheuble, V., & Beauducel, A. (2020). Individual differences of conflict monitoring and feedback processing during reinforcement learning in a mock forensic context. *Cognitive, Affective, & Behavioral Neuroscience*, *20*. https://doi.org/10.3758/s13415-020-00776-7

Li, S.-C., & Rieckmann, A. (2014). Neuromodulation and aging: Implications of aging neuronal gain control on cognition. *Current Opinion in Neurobiology*, *29*, 148–158. https://doi.org/10.1016/j.conb.2014.07.009

Lighthall, N. R., Pearson, J. M., Huettel, S. A., & Cabeza, R. (2018). Feedback-based learning in aging: Contributions and trajectories of change in striatal and hippocampal systems. *Journal of Neuroscience*, *38*, 8453–8462. https://doi.org/10.1523/JNEUROSCI.0769-18.2018

Lin, H., & Liang, J. (2021). Working memory load reduces the processing of outcome evaluation involving others but not oneself: Event-related potential evidence. *Psychophysiology*, *58*, e13938. https://doi.org/10.1111/psyp.13938

Liu, Y., & Gehring, W. J. (2009). Loss feedback negativity elicited by single- versus conjoined-feature stimuli. *NeuroReport*, *20*. https://journals.lww.com/neuroreport/fulltext/2009/04220/loss_feedback_negativity_elicited_by_single_.19.aspx

Liu, Y., Nelson, L. D., Bernat, E. M., & Gehring, W. J. (2014). Perceptual properties of feedback stimuli influence the feedback-related negativity in the flanker gambling task. *Psychophysiology*, *51*, 782–788. https://doi.org/10.1111/psyp.12216

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00213

Lubitz, A. F., Niedeggen, M., & Feser, M. (2017). Aging and working memory performance: Electrophysiological correlates of high and low performing elderly. *Neuropsychologia*, *106*, 42–51. https://doi.org/10.1016/j.neuropsychologia.2017.09.002

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). *Psychophysiology*, *54*, 146–157. https://doi.org/10.1111/psyp.12639

Luck, S. J., & Kappenmann, E. S. (2012). The oxford handbook of event-related potential components. In S. J. Luck & E. S. Kappenman (Eds.), *The Oxford handbook of event-related potential components.* (pp. 641, xxii, 641–xxii). Oxford University Press.

Luft, C. (2014). Learning from feedback: The neural mechanisms of feedback processing facilitating better performance. *Behavioural Brain Research*, *261*. https://doi.org/10.1016/j.bbr.2013.12.043

Martín, R. S. (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

Mather, M. (2012). The emotion paradox in the aging brain. *Annals of the New York Academy of Sciences*, *1251*, 33–49. https://doi.org/10.1111/j.1749-6632.2012.06471.x

Mather, M., Canli, T., English, T., Whitfield, S., Wais, P., Ochsner, K., John, D. E. G., & Carstensen, L. L. (2004). Amygdala responses to emotionally valenced stimuli in older and younger adults. *Psychological Science*, *15*, 259–263. https://doi.org/10.1111/j.0956-7976.2004.00662.x

Mather, M., & Carstensen, L. L. (2005). Aging and motivated cognition: The positivity effect in attention and memory. *Trends in Cognitive Sciences*, *9*, 496–502. https://doi.org/10.1016/j.tics.2005.08.005

Mathewson, K. J., Dywan, J., Snyder, P. J., Tays, W. J., & Segalowitz, S. J. (2008). Aging and electrocortical response to error feedback during a spatial learning task. *Psychophysiology*, *45*, 936–948. https://doi.org/10.1111/j.1469-8986.2008.00699.x

Matyjek, M., Meliss, S., Dziobek, I., & Murayama, K. (2020). A multidimensional view on social and non-social rewards. In *Frontiers in Psychiatry* (Vol. 11). https://www.frontiersin.org/articles/10.3389/fpsyt.2020.00818

McCarthy, G., & Donchin, E. (1981). A metric for thought: A comparison of P300 latency and reaction time. *Science*, *211*, 77–80. https://doi.org/10.1126/science.7444452

McCarthy, G., Puce, A., Gore, J. C., & Allison, T. (1997). Face-specific processing in the human fusiform gyrus. *Journal of cognitive neuroscience*, 9(5), 605–610. https://doi.org/10.1162/jocn.1997.9.5.605

Mecklinger, A., Ullsperger, P., Mölle, M., & Grune, K. (1994). Event-related potentials indicate information extraction in a comparative judgement task. *Psychophysiology*, *31*, 23–28. https://doi.org/10.1111/j.1469-8986.1994.tb01021.x

Meel, C. S. V., & Heijningen, C. A. A. V. (2010). The effect of interpersonal competition on monitoring internal and external error feedback. *Psychophysiology*, *47*, 213–222. https://doi.org/10.1111/j.1469-8986.2009.00944.x

Mell, T., Heekeren, H. R., Marschner, A., Wartenburger, I., Villringer, A., & Reischies, F. M. (2005). Effect of aging on stimulus-reward association learning. *Neuropsychologia*, *43*, 554–563. https://doi.org/10.1016/j.neuropsychologia.2004.07.010

Mies, G. W., Veen, F. M. V. der, Tulen, J. H. M., Hengeveld, M. W., & Molen, M. W. V. der. (2011). Cardiac and electrophysiological responses to valid and invalid feedback in a time-estimation task. *Journal of Psychophysiology*, *25*, 131–142. https://doi.org/10.1027/0269-8803/a000049

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*, 788–798. https://doi.org/10.1162/jocn.1997.9.6.788

Molen, M. J. W. van der, Dekkers, L. M. S., Westenberg, P. M., Veen, F. M. van der, & Molen, M. W. van der. (2017). Why don't you like me? Midfrontal theta power in response to unexpected peer rejection feedback. *NeuroImage*, *146*, 474–483. https://doi.org/10.1016/j.neuroimage.2016.08.045

Morr, M., Liu, X., Hurlemann, R., Becker, B., & Scheele, D. (2022). Chronic loneliness: Neurocognitive mechanisms and interventions. *Psychotherapy and Psychosomatics*, *91*, 227–237. https://doi.org/10.1159/000524157

Nagel, I. E., Preuschhof, C., Li, S.-C., Nyberg, L., Bäckman, L., Lindenberger, U., & Heekeren, H. R. (2009). Performance level modulates adult age differences in brain activation during spatial working memory. *Proceedings of the National Academy of Sciences of the United States of America*, *106*, 22552–22557. https://doi.org/10.1073/pnas.0908238106

Nashiro, K., Mather, M., Gorlick, M., & Nga, L. (2011). Negative emotional outcomes impair older adults' reversal learning. *Cognition & Emotion*, *25*, 1014–1028. https://doi.org/10.1080/02699931.2010.542999

Neufeld, N., Parker, A. F., Kwan, H., Mazerolle, E. L., & Gawryluk, J. R. (2022). Longitudinal changes in grey matter and cognitive performance over four years of healthy aging. *Neuroimage: Reports*, *2*, 100140. https://doi.org/10.1016/j.ynirp.2022.100140

Nieuwenhuis, S., Heslenfeld, D. J., Geusau, N. J. A. von, Mars, R. B., Holroyd, C. B., & Yeung, N. (2005). Activity in human reward-sensitive brain areas is strongly context dependent. *NeuroImage*, *25*, 1302–1309. https://doi.org/10.1016/j.neuroimage.2004.12.043

Nieuwenhuis, S., Holroyd, C. B., Mol, N., & Coles, M. G. H. (2004). Reinforcement-related brain potentials from medial frontal cortex: Origins and functional significance. *Neuroscience & Biobehavioral Reviews*, *28*, 441–448. https://doi.org/10.1016/j.neubiorev.2004.05.003

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

Oldfield, R. C. (1971). The assessment and analysis of handedness: The edinburgh inventory. *Neuropsychologia*, *9*, 97–113. https://doi.org/10.1016/0028-3932(71)90067-4

Oliveira, F. T. P., McDonald, J. J., & Goodman, D. (2007). Performance monitoring in the anterior cingulate is not all error related: Expectancy deviation and the representation of action-outcome associations. *Journal of Cognitive Neuroscience*, *19*, 1994–2004. https://doi.org/10.1162/jocn.2007.19.12.1994

Olofsson, J. K., Nordin, S., Sequeira, H., & Polich, J. (2008). Affective picture processing: An integrative review of ERP findings. *Biological Psychology*, *77*, 247–265. https://doi.org/10.1016/j.biopsycho.2007.11.006

Opitz, B., Ferdinand, N., & Mecklinger, A. (2011). Timing matters: The impact of immediate and delayed feedback on artificial language learning. In *Frontiers in Human Neuroscience* (Vol. 5). https://www.frontiersin.org/article/10.3389/fnhum.2011.00008

Orgeta, V., & Phillips, L. H. (2007). Effects of age and emotional intensity on the recognition of facial emotion. *Experimental Aging Research*, *34*, 63–79. https://doi.org/10.1080/03610730701762047

Park, D. C., Polk, T. A., Mikels, J. A., Taylor, S. F., & Marshuetz, C. (2001). Cerebral aging: Integration of brain and behavioral models of cognitive function. *Dialogues in Clinical Neuroscience*, *3*, 151–165. https://doi.org/10.31887/DCNS.2001.3.3/dcpark

Paul, K., Angus, D. J., Bublatzky, F., Wüllhorst, R., Endrass, T., Greenwood, L.-M., Hajcak, G., Jack, B. N., Korinth, S. P., Kroczek, L. O. H., Lucero, B., Mundorf, A., Nolden, S., Peterburs, J., Pfabigan, D. M., Schettino, A., Severo, M. C., Shing, Y. L., Turan, G., … Pourtois, G. (2025). Revisiting the electrophysiological correlates of valence and

expectancy in reward processing – a multi-lab replication. *Cortex*, *184*, 150–171. https://doi.org/10.1016/j.cortex.2024.12.017

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*, e13481. https://doi.org/10.1111/psyp.13481

Paulus, C. G. (2009). *Der saarbrücker persönlichkeitsfragebogen (IRI) zur messung von empathie: Psychometrische evaluation der deutschen version des interpersonal reactivity index*. https://doi.org/10.23668/psycharchives.9249

Peters, A., Helming, H., Bruchmann, M., Wiegandt, A., Straube, T., & Schindler, S. (2024). How and when social evaluative feedback is processed in the brain: A systematic review on ERP studies. *Cortex*, *173*, 187–207. https://doi.org/10.1016/j.cortex.2024.02.003

Pfabigan, D. M., Alexopoulos, J., Bauer, H., & Sailer, U. (2011). Manipulation of feedback expectancy and valence induces negative and positive reward prediction error signals manifest in event-related brain potentials. *Psychophysiology*, *48*, 656–664. https://doi.org/10.1111/j.1469-8986.2010.01136.x

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

Pfabigan, D. M., & Han, S. (2019). Converging electrophysiological evidence for a processing advantage of social over nonsocial feedback. *Cognitive, Affective, & Behavioral Neuroscience*, *19*, 1170–1183. https://api.semanticscholar.org/CorpusID:197422382

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

Pfabigan, D. M., Wucherer, A. M., Wang, X., Pan, X., Lamm, C., & Han, S. (2018). Cultural influences on the processing of social comparison feedback signals—an ERP study. *Social*

Cognitive and Affective Neuroscience, *13*, 1317–1326. https://doi.org/10.1093/scan/nsy097

Pfabigan, D. M., Zeiler, M., Lamm, C., & Sailer, U. (2014). Blocked versus randomized presentation modes differentially modulate feedback-related negativity and P3b amplitudes. *Clinical Neurophysiology*, *125*, 715–726. https://doi.org/10.1016/j.clinph.2013.09.029

Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., Johnson, R., Jr, Miller, G. A., Ritter, W., Ruchkin, D. S., Rugg, M. D., & Taylor, M. J. (2000). Guidelines for using human event-related potentials to study cognition: recording standards and publication criteria. *Psychophysiology*, 37(2), 127–152.

Pietschmann, M., Endrass, T., Czerwon, B., & Kathmann, N. (2011). Aging, probabilistic learning and performance monitoring. *Biological Psychology*, *86*, 74–82. https://doi.org/10.1016/j.biopsycho.2010.10.009

Pietschmann, M., Simon, K., Endrass, T., & Kathmann, N. (2008). Changes of performance monitoring with learning in older and younger adults. *Psychophysiology*, *45*, 559–568. https://doi.org/10.1111/j.1469-8986.2008.00651.x

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, *198*, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026

Polich, J. (1987). Task difficulty, probability, and inter-stimulus interval as determinants of P300 from auditory stimuli. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, *68*, 311–320. https://doi.org/10.1016/0168-5597(87)90052-9

Polich, J. (2004). Clinical application of the P300 event-related brain potential. *Physical Medicine and Rehabilitation Clinics*, *15*, 133–161. https://doi.org/10.1016/S1047-9651(03)00109-8

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*, 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019

Polich, J., & Criado, J. R. (2006). Neuropsychology and neuropharmacology of P3a and P3b. *International Journal of Psychophysiology*, *60*, 172–185. https://doi.org/10.1016/j.ijpsycho.2005.12.012

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

Psychology Software Tools, Inc. [E-Prime 3.0]. (2016). Retrieved from https://support.pstnet.com/.

Rak, N., Bellebaum, C., & Thoma, P. (2013). Empathy and feedback processing in active and observational learning. *Cognitive, Affective, & Behavioral Neuroscience*, *13*, 869–884. https://doi.org/10.3758/s13415-013-0187-1

Raz, N., & Lindenberger, U. (2011). Only time will tell: Cross-sectional studies offer no solution to the age–brain–cognition triangle: Comment on. *Psychological Bulletin*, *137*, 790–795. https://doi.org/10.1037/a0024503

Raz, N., & Rodrigue, K. M. (2006). Differential aging of the brain: Patterns, cognitive correlates and modifiers. *Neuroscience & Biobehavioral Reviews*, *30*, 730–748. https://doi.org/10.1016/j.neubiorev.2006.07.001

Reed, A. E., & Carstensen, L. L. (2012). The theory behind the age-related positivity effect. *Frontiers in Psychology*, *Volume 3 - 2012*. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2012.00339

Reed, A. E., Chan, L., & Mikels, J. A. (2014). Meta-analysis of the age-related positivity effect: Age differences in preferences for positive over negative information. *Psychology and Aging*, *29*, 1–15. https://doi.org/10.1037/a0035194

Reuter-Lorenz, P. A., & Cappell, K. A. (2008). Neurocognitive aging and the compensation hypothesis. *Current Directions in Psychological Science*, *17*, 177–182. https://doi.org/10.1111/j.1467-8721.2008.00570.x

Reuter-Lorenz, P. A., Jonides, J., Smith, E. E., Hartley, A., Miller, A., Marshuetz, C., & Koeppe, R. A. (2000). Age differences in the frontal lateralization of verbal and spatial working memory revealed by PET. *Journal of Cognitive Neuroscience*, *12*, 174–187. https://doi.org/10.1162/089892900561814

Reuter-Lorenz, P. A., & Park, D. C. (2014). How does it STAC up? Revisiting the scaffolding theory of aging and cognition. *Neuropsychology Review*, *24*, 355–370. https://doi.org/10.1007/s11065-014-9270-9

Rolls, E. T. (2000). The orbitofrontal cortex and reward. *Cerebral Cortex (New York, N.Y. : 1991)*, *10*, 284–294. https://doi.org/10.1093/cercor/10.3.284

Rossion, B., & Pourtois, G. (2004). Revisiting snodgrass and vanderwart's object pictorial set: The role of surface detail in basic-level object recognition. *Perception*, *33*, 217–236. https://doi.org/10.1068/p5117

Ruff, C. C., & Fehr, E. (2014). The neurobiology of rewards and values in social decision making. *Nature Reviews Neuroscience*, *15*, 549–562. https://doi.org/10.1038/nrn3776

Ruffman, T., Henry, J. D., Livingstone, V., & Phillips, L. H. (2008). A meta-analytic review of emotion recognition and aging: Implications for neuropsychological models of aging. *Neuroscience & Biobehavioral Reviews*, *32*, 863–881. https://api.semanticscholar.org/CorpusID:8981189

Ryff, C. D. (2013). Psychological well-being revisited: Advances in the science and practice of eudaimonia. *Psychotherapy and Psychosomatics*, *83*, 10–28. https://doi.org/10.1159/000353263

Sailer, U., Wurm, F., & Pfabigan, D. M. (2024). Social and non-social feedback stimuli lead to comparable levels of reward learning and reward responsiveness in an online probabilistic reward task. *Behavior Research Methods*, *56*, 5161–5177. https://doi.org/10.3758/s13428-023-02255-6

Salis, F., Costaggiu, D., & Mandas, A. (2023). Mini-mental state examination: Optimal cut-off levels for mild and severe cognitive impairment. *Geriatrics*, *8*. https://doi.org/10.3390/geriatrics8010012

Salthouse, T. (2010). Selective review of aging. *Journal of the International Neuropsychological Society : JINS*, *16*, 754–760. https://doi.org/10.1017/S1355617710000706

Salthouse, T. A. (2004). What and when of cognitive aging. *Current Directions in Psychological Science*, *13*, 140–144. https://doi.org/10.1111/j.0963-7214.2004.00293.x

Samanez-Larkin, G. R., Worthy, D. A., Mata, R., McClure, S. M., & Knutson, B. (2014). Adult age differences in frontostriatal representation of prediction error but not reward outcome. *Cognitive, Affective, & Behavioral Neuroscience*, *14*, 672–682. https://doi.org/10.3758/s13415-014-0297-4

Sambrook, T., & Goslin, J. (2014). A neural reward prediction error revealed by a meta-analysis of ERPs using great grand averages. *Psychological Bulletin*, *141*. https://doi.org/10.1037/bul0000006

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*, 407–411. https://doi.org/10.1097/00001756-200503150-00020

Schmitt, H., Ferdinand, N. K., & Kray, J. (2014a). Age-differential effects on updating cue information: Evidence from event-related potentials. *Cognitive, Affective, & Behavioral Neuroscience*, *14*, 1115–1131. https://doi.org/10.3758/s13415-014-0268-9

Schmitt, H., Ferdinand, N. K., & Kray, J. (2015). The influence of monetary incentives on context processing in younger and older adults: An event-related potential study. *Cognitive, Affective and Behavioral Neuroscience*, *15*, 416–434. https://doi.org/10.3758/s13415-015-0335-x

Schmitt, H., Wolff, M. C., Ferdinand, N. K., & Kray, J. (2014b). Age differences in the processing of context information. *Journal of Psychophysiology*, *28*, 202–214. https://doi.org/10.1027/0269-8803/a000126

Schmücker, L. J. C., & Pfabigan, D. M. (2025). *How unknown social and non-social stimuli influence EEG responses to feedback* [Preregistration]. OSF. https://doi.org/10.17605/OSF.IO/ZJYFD

Schulreich, S., Pfabigan, D. M., Derntl, B., & Sailer, U. (2013). Fearless dominance and reduced feedback-related negativity amplitudes in a time-estimation task – further neuroscientific evidence for dual-process models of psychopathy. *Biological Psychology*, *93*, 352–363. https://doi.org/10.1016/j.biopsycho.2013.04.004

Schultz, W. (1986). Responses of midbrain dopamine neurons to behavioral trigger stimuli in the monkey. *Journal of Neurophysiology*, *56*, 1439–1461. https://doi.org/10.1152/jn.1986.56.5.1439

Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron*, *36*, 241–263. https://doi.org/10.1016/s0896-6273(02)00967-4

Segalowitz, S. J., Wintink, A. J., & Cudmore, L. J. (2001). P3 topographical change with task familiarization and task complexity. *Cognitive Brain Research*, *12*, 451–457. https://doi.org/10.1016/S0926-6410(01)00082-9

Sergent, J., & Signoret, J. L. (1992). Functional and anatomical decomposition of face processing: evidence from prosopagnosia and PET study of normal subjects. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *335*(1273), 55–62. https://doi.org/10.1098/rstb.1992.0007

Severo, M. C., Paul, K., Walentowska, W., Moors, A., & Pourtois, G. (2020). Neurophysiological evidence for evaluative feedback processing depending on goal relevance. *NeuroImage*, *215*, 116857. https://doi.org/10.1016/j.neuroimage.2020.116857

Shigeto, H., Ishiguro, J., & Nittono, H. (2011). Effects of visual stimulus complexity on event-related brain potentials and viewing duration in a free-viewing task. *Neuroscience Letters*, *497*, 85–89. https://doi.org/10.1016/j.neulet.2011.04.035

Shiwei, J. I. A., Congcong, Q. I., CHEN, L., & Yanju, R. E. N. (2022). The effect of working memory load on feedback processing: Evidence from an event-related potentials (ERP)

study. *Acta Psychologica Sinica, 54*, 248–258. https://doi.org/10.3724/SP.J.1041.2022.00248

Skinner, B. F. (1963). Operant behavior. *American Psychologist*, *18*, 503–515. https://doi.org/10.1037/h0045185

Slessor, G., Insch, P., Donaldson, I., Sciaponaite, V., Adamowicz, M., & Phillips, L. H. (2022). Adult age differences in using information from the eyes and mouth to make decisions about others' emotions. *The Journals of Gerontology: Series B*, *77*, 2241–2251. https://doi.org/10.1093/geronb/gbac097

Snodgrass, J. G., & Vanderwart, M. (1980). A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity. *Journal of Experimental Psychology. Human Learning and Memory*, *6 2*, 174–215.

Somon, B., Campagne, A., Delorme, A., & Berberian, B. (2019). Evaluation of performance monitoring ERPs through difficulty manipulation in a response-feedback paradigm. *Brain Research*, *1704*, 196–206. https://doi.org/10.1016/j.brainres.2018.10.007

Stavropoulos, K. K. M., & Carver, L. J. (2014). Reward anticipation and processing of social versus nonsocial stimuli in children with and without autism spectrum disorders. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *55*, 1398–1408. https://doi.org/10.1111/jcpp.12270

Stone, A. A., Schwartz, J. E., Broderick, J. E., & Deaton, A. (2010). A snapshot of the age distribution of psychological well-being in the united states. *Proceedings of the National Academy of Sciences*, *107*, 9985–9990. https://doi.org/10.1073/pnas.1003744107

Sullivan, E. V., Marsh, L., Mathalon, D. H., Lim, K. O., & Pfefferbaum, A. (1995). Age-related decline in MRI volumes of temporal lobe gray matter but not hippocampus. *Neurobiology of Aging*, *16*, 591–606. https://doi.org/10.1016/0197-4580(95)00074-O

Sullivan, S., & Ruffman, T. (2004). EMOTION RECOGNITION DEFICITS IN THE ELDERLY. *International Journal of Neuroscience*, *114*, 403–432. https://doi.org/10.1080/00207450490270901

Sutton, S., Braren, M., Zubin, J., & John, E. R. (1965). Evoked-potential correlates of stimulus uncertainty. *Science*, *150*, 1187–1188. https://doi.org/10.1126/science.150.3700.1187

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction*, *4*, 295–312. https://doi.org/10.1016/0959-4752(94)90003-5

Swirsky, L. T., Sparrow, E. P., Sullivan, M. D., Valenzano, S. L., Chowdhury, S., & Spaniol, J. (2023). Age differences in motivated cognition: A meta-analysis. *The Journals of Gerontology: Series B*, *78*, 1169–1181. https://doi.org/10.1093/geronb/gbad049

Talmi, D., Atkinson, R., & El-Deredy, W. (2013). The feedback-related negativity signals salience prediction errors, not reward prediction errors. *The Journal of Neuroscience*, *33*, 8264. https://doi.org/10.1523/JNEUROSCI.5695-12.2013

Team, R. C. (2020). R: A language and environment for statistical computing. In *R Foundation for Statistical Computing* (Vol. 3, pp. https://www.R–project.org). R Foundation for Statistical Computing. https://www.r-project.org/ http://www.r-project.org

The Mathworks Inc. (2022). *MATLAB version: 9.13.0 (R2022b)*. The MathWorks Inc. https://www.mathworks.com

Thoma, P., & Bellebaum, C. (2012). Your error's got me feeling – how empathy relates to the electrophysiological correlates of performance monitoring. *Frontiers in Human Neuroscience*, *6*. https://www.frontiersin.org/articles/10.3389/fnhum.2012.00135

Thompson, R. (1994). Emotion regulation: A theme in search of definition. *Monographs of the Society for Research in Child Development*, *59*, 25–52. https://doi.org/10.1111/j.1540-5834.1994.tb01276.x

Thorndike, E. L. (1911). The law of effect. *The American Journal of Psychology*, *39*, 212–222. https://doi.org/10.2307/1415413

Tregellas, J. R., Davalos, D. B., & Rojas, D. C. (2006). Effect of task difficulty on the functional anatomy of temporal processing. *NeuroImage*, *32*, 307–315. https://doi.org/10.1016/j.neuroimage.2006.02.036

Ullsperger, M. (2024). Beyond peaks and troughs: Multiplexed performance monitoring signals in the EEG. *Psychophysiology*, *61*, e14553. https://doi.org/10.1111/psyp.14553

Ullsperger, M., Danielmeier, C., & Jocham, G. (2014). Neurophysiology of performance monitoring and adaptive behavior. *Physiological Reviews*, *94*, 35–79.

United Nations. (2023). *World social report 2023: Leaving no one behind in an ageing world*. Nations United, Department of Economic; Social Affairs; United Nations. https://social.desa.un.org/publications/undesa-world-social-report-2023

Vassena, E., Deraeve, J., & Alexander, W. H. (2020). Surprise, value and control in anterior cingulate cortex during speeded decision-making. *Nature Human Behaviour*, *4*, 412–422. https://doi.org/10.1038/s41562-019-0801-5

Verhaeghen, P., & Salthouse, T. (1997). Meta-analyses of age-cognition relations in adulthood: Estimates of linear and nonlinear age effects and structural models. *Psychological Bulletin*, *122*, 231–249. https://doi.org/10.1037//0033-2909.122.3.231

Voegler, R., Peterburs, J., Bellebaum, C., & Straube, T. (2019). Modulation of feedback processing by social context in social anxiety disorder (SAD)–an event-related potentials (ERPs) study. *Scientific Reports*, *9*, 1–14. https://doi.org/10.1038/s41598-019-41268-0

Volkow, N. D., Ding, Y.-S., Fowler, J. S., Wang, G.-J., Logan, J., Gatley, S. J., Hitzemann, R., Smith, G., Fields, S. D., & Gur, R. (1996). Dopamine transporters decrease with age. *Journal of Nuclear Medicine*, *37*, 554. http://jnm.snmjournals.org/content/37/4/554.abstract

Walentowska, W., Moors, A., Paul, K., & Pourtois, G. (2016). Goal relevance influences performance monitoring at the level of the FRN and P3 components. *Psychophysiology*, *53*, 1020–1033. https://doi.org/10.1111/psyp.12651

Walhovd, K. B., Fjell, A. M., Reinvang, I., Lundervold, A., Dale, A. M., Eilertsen, D. E., Quinn, B. T., Salat, D., Makris, N., & Fischl, B. (2005). Effects of age on volumes of cortex, white matter and subcortical structures. *Neurobiology of Aging*, *26*, 1261–1270. https://doi.org/10.1016/j.neurobiolaging.2005.05.020

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*, 1870–1884. https://doi.org/10.1016/j.neubiorev.2012.05.008

Weinberg, A., & Hajcak, G. (2010). Beyond good and evil: The time-course of neural activity elicited by specific picture content. *Emotion (Washington, D.C.)*, *10*, 767–782. https://doi.org/10.1037/a0020242

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

Weiß, M., Gutzeit, J., Rodrigues, J., Mussel, P., & Hewig, J. (2019). Do emojis influence social interactions? Neural and behavioral responses to affective emojis in bargaining situations. *Psychophysiology*, *56*, e13321. https://doi.org/10.1111/psyp.13321

Weiß, M., Rodrigues, J., Boschet, J. M., Pittig, A., Mussel, P., & Hewig, J. (2020). How depressive symptoms and fear of negative evaluation affect feedback evaluation in social decision-making. *Journal of Affective Disorders Reports*, *1*, 100004. https://doi.org/10.1016/j.jadr.2020.100004

Wessel, J. R., Danielmeier, C., Morton, J. B., & Ullsperger, M. (2012). Surprise and error: Common neuronal architecture for the processing of errors and novelty. *The Journal of Neuroscience*, *32*, 7528. https://doi.org/10.1523/JNEUROSCI.6352-11.2012

West, R. L. (1996). An application of prefrontal cortex function theory to cognitive aging. *Psychological Bulletin*, *120*, 272–292. https://doi.org/10.1037/0033-2909.120.2.272

West, R., & Huet, A. (2020). The effect of aging on the ERP correlates of feedback processing in the probabilistic selection task. *Brain Sciences*, *10*. https://doi.org/10.3390/brainsci10010040

Westfall, J. (2016). PANGEA: Power Analysis for GEneral Anova designs (working paper). https://github.com/jake-westfall/pangea.

Wild-Wall, N., Willemssen, R., & Falkenstein, M. (2009). Feedback-related processes during a time-production task in young and older adults. *Clinical Neurophysiology*, *120*, 407–413. https://doi.org/10.1016/j.clinph.2008.11.007

Wurm, F., Ernst, B., & Steinhauser, M. (2020). The influence of internal models on feedback-related brain activity. *Cognitive, Affective, & Behavioral Neuroscience*, *20*, 1070–1089. https://doi.org/10.3758/s13415-020-00820-6

Yeung, N., Botvinick, M. M., & Cohen, J. D. (2004). The neural basis of error detection: Conflict monitoring and the error-related negativity. *Psychological Review*, *111*, 931–959. https://doi.org/10.1037/0033-295x.111.4.939

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*, 535–544. https://doi.org/10.1093/cercor/bhh153

Zhang, Y., Liang, Y., & Gu, Y. (2025). The dopaminergic system and alzheimer's disease. *Neural Regeneration Research*, *20*. https://journals.lww.com/nrronline/fulltext/2025/09000/the_dopaminergic_system_and_alzheimer_s_disease.5.aspx

9 Appendix

9.1 Study 1: Supplementary Material

Table S1. *Mean number (Standard Deviations) of included trials for Group x Learning Half x Feedback Condition x Valence.*

Variable	Easy Group		Difficult Group	
	1st Learning Half	2nd Learning Half	1st Learning Half	2nd Learning Half
Emotional correct	127.90 (12.05)	145.23 (8.38)	102.00 (16.79)	104.57 (14.02)
Emotional incorrect	27.82 (8.47)	10.95 (4.97)	45.86 (13.35)	49.67 (14.67)
Non-emotional correct	118.36 (13.09)	139.50 (9.41)	126.24 (16.59)	123.33 (18.27)
Non-emotional incorrect	32.82 (9.97)	16.82 (8.61)	29.81 (19.36)	29.24 (14.68)

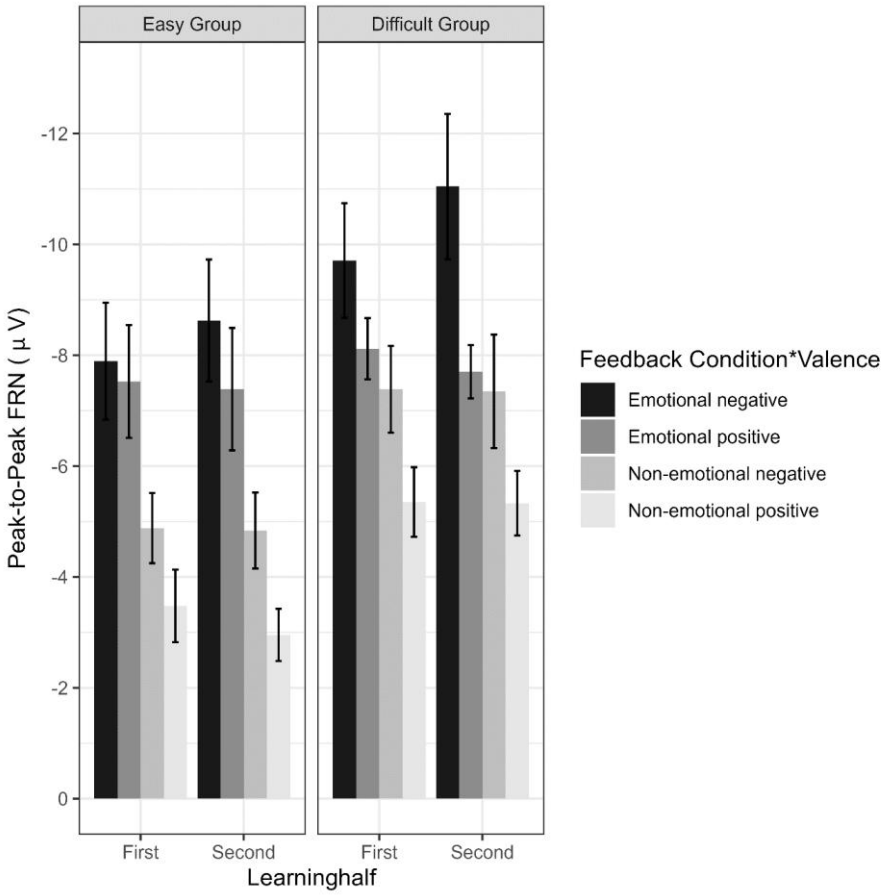
Exploratory ERP Analyses In this exploratory analysis, we were interested in investigating whether learning half has an impact on the feedback-locked ERPs. Due to the low trial numbers in certain conditions (see table S1), the following analyses are likely not reliable and should be interpreted with caution.

Peak-to-Peak FRN We conducted an exploratory peak-to-peak FRN ANOVA at channel FCz, incorporating the between-subject factor Task Difficulty (easy, difficult) and the within-subject factors Feedback Condition (emotional, non-emotional), Valence (positive, negative), and Learning Half (first, second). Significant main effects and interactions are reported in Table S2, and a graphical overview is provided in Figure S1. Including Learning Half as a factor did not yield any additional significant effects or interactions (all *p*-values >.15).

Table S2. *Effects of the Peak-to-peak FRN ANOVA.*

Measure	DFn	DFd	F-value	p-value	p<.05	η_p^2
Difficulty	1	41	3.67	0.06		0.08
Feedback Condition	**1**	**41**	**62.64**	**0.00000000087**	*****	**0.60**
Valence	**1**	**41**	**25.82**	**0.00000862000**	*****	**0.38**
Learning Half	1	41	0.19	0.66		0.01
Difficulty x Feedback Condition	1	41	1.52	0.22		0.04
Difficulty x Valence	1	41	2.24	0.14		0.05
Difficulty x Learning Half	1	41	0.17	0.68		0.00
Feedback Condition x Valence	1	41	0.09	0.76		0.00
Feedback Condition x Learning Half	1	41	1.69	0.20		0.04
Valence x Learning Half	1	41	2.17	0.15		0.05
Difficulty x Feedback Condition x Valence	1	41	0.97	0.33		0.02
Difficulty x Feedback Condition x Learning Half	1	41	0.01	0.91		0.00
Difficulty x Valence x Learning Half	1	41	0.03	0.86		0.00
Feedback Condition x Valence x Learning Half	1	41	2.13	0.15		0.05
Difficulty x Feedback Condition x Valence x Learning Half	1	41	0.89	0.36		0.02

Figure S1. *Graphical illustration for the exploratory peak-to-peak FRN analyses***.**



Mean P3b We performed an exploratory mean P3b ANOVA with the between-subject factors Task Difficulty (easy, difficult) and the within-subject factors Feedback Condition (emotional, non-emotional), Valence (positive, negative), Learning Half (first, second) and Channel (Fz, Cz, Pz). The significant main effects and interactions can be found in table S3. Notably, no interactions of the factor Learning Half were found with Feedback Condition. Also, no interactions including Feedback Condition x Task Difficulty emerged. However, Learning Half did interact with Task Difficulty.

Table S3. *Results of the ANOVA on the mean P3b amplitude.*

Measure	DFn	DFd	F-value	p-value	p<.05	η_p^2
Difficulty	1	41	3.27	0.08		0.07
Valence	1	41	1.14	0.29		0.03
Feedback Condition	**1**	**41**	**5.39**	**0.025**	*****	**0.12**
Channel	**1.55**	**63.63**	**22.19**	**0.000000507**	*****	**0.35**
Learning Half	**1**	**41**	**23.36**	**0.0000191**	*****	**0.36**
Difficulty x Valence	1	41	0.01	0.94		0.00
Difficulty x Feedback Condition	1	41	0.98	0.33		0.02
Difficulty x Feedback Condition	1	41	0.98	0.33		0.02
Difficulty x Channel	**1.55**	**63.63**	**7.39**	**0.003**	*****	**0.15**
Difficulty x Learning Half	1	41	1.69	0.20		0.04
Valence x Feedback Condition	1	41	2.04	0.16		0.05
Valence x Channel	**2**	**82**	**5.58**	**0.005**	*****	**0.12**
Feedback Condition x Channel	**1.72**	**70.39**	**11.45**	**0.000115**	*****	**0.22**
Valence x Learning Half	**1**	**41**	**5.02**	**0.031**	*****	**0.11**
Feedback Condition x Learning Half	1	41	0.06	0.82		0.00
Channel x Learning Half	**2**	**82**	**22.39**	**0.0000000175**	*****	**0.35**
Difficulty x Valence x Feedback Condition	1	41	0.33	0.57		0.01

Measure	DFn	DFd	F-value	p-value	p<.05	η_p^2
Difficulty x Valence x Channel	2	82	0.01	0.98		0.00
Difficulty x Feedback Condition x Channel	1.72	70.39	0.97	0.37		0.02
Difficulty x Valence x Learning Half	**1**	**41**	**5.17**	**0.028**	*****	**0.11**
Difficulty x Feedback Condition x Learning Half	1	41	0.65	0.43		0.02
Difficulty x Channel x Learning Half	**2**	**82**	**3.19**	**0.046**	*****	**0.07**
Valence x Feedback Condition x Channel	1.56	64.11	0.94	0.37		0.02
Valence x Feedback Condition x Learning Half	1	41	1.19	0.28		0.03
Valence x Channel x Learning Half	**2**	**82**	**6.34**	**0.003**	*****	**0.13**
Feedback Condition x Channel x Learning Half	2	82	2.47	0.09		0.06
Difficulty x Valence x Feedback Condition x Channel	1.56	64.11	0.21	0.76		0.01
Difficulty x Valence x Feedback Condition x Learning Half	1	41	1.89	0.18		0.04
Difficulty x Valence x Channel x Learning Half	**2**	**82**	**3.57**	**0.033**	*****	**0.08**
Difficulty x Feedback Condition x Channel x Learning Half	2	82	1.12	0.33		0.03

Valence x Feedback Condition x Channel x Learning Half	1.58	64.64	0.49	0.57	0.01
Difficulty x Valence x Feedback Condition x Channel x Learning Half	1.58	64.64	0.83	0.42	0.02

To explain the significant four-way interaction between Difficulty, Valence, Channel, and Learning Half, we conducted separate ANOVAs for each difficulty condition. The analysis for the easy group revealed significant main effects for Channel ($F(2,42) = 19.74$, $p < .001$, $\eta_p^2 = .48$), Learning Half ($F(1,21) = 14.36$, $p = .001$, $\eta_p^2 = .41$), a two-way interaction between Valence and Learning Half ($F(1,21) = 9.47$, $p = .006$, $\eta_p^2 = .31$), and a three-way interaction between Valence and Channel and Learning Half ($F(2,42) = 6.94$, $p = .002$, $\eta_p^2 = .25$). To resolve the three-way interaction between Valence, Channel, and Learning Half in the easy group, we conducted Bonferroni-corrected Post hoc tests. These showed a clear parietal distribution of the P3b in Learning Half 1 (positive feedback: Fz vs. Cz: $t(85.99) = -3.59$, $p = .002$, and Cz vs. Pz: $t(85.83) = -4.57$, $p < .001$, negative Feedback: Fz vs. Cz: $t(85.80) = -2.74$, $p = .022$, and Cz vs. Pz: $t(85.90) = -3.07$, $p = .009$), which became even more focused on parietal electrode sites in Learning Half 2 (positive feedback: Fz vs. Cz: $p = .149$, and Cz vs. Pz: $t(85.92) = -4.91$, $p < .001$, negative Feedback: Fz vs. Cz: $p = .948$, and Cz vs. Pz: $t(85.68) = -4.37$, $p < .001$). Differences between the first and the second half were significant, however, only for negative feedback at electrodes Cz ($t(85.85) = 4.53$, $p < .001$) and Pz ($t(84.49) = 2.84$, $p = .005$). Together, these effects may suggest a learning effect, indicating that working memory updating requires fewer frontal resources as learning progresses, with this reduction being particularly pronounced in response to negative feedback. The analysis for the difficult group revealed significant main effects for Channel ($F(2,40) = 10.86$, $p < .001$, $\eta_p^2 = .35$), and Learning Half ($F(1,20) = 9.51$, $p = .006$, $\eta_p^2 = .32$), and a significant interaction between Channel and Learning Half ($F(2,40) = 8.68$, $p < .001$, $\eta_p^2 = .30$). To explain the two-way interaction between Channel and Learning Half in the difficult condition, we also calculated Bonferroni-corrected Post hoc tests. These tests revealed a centro-parietal distribution of the P3b in the first and the second learning half (Learning Half 1: Fz vs. Cz: $t(83) = -10.04$, $p < .001$), and Cz vs. Pz*:* $p = .245$, Learning Half 2: Fz vs. Cz: $t(83) = -8.04$, $p < .001$), and Cz vs. Pz*:* $p = .278$). Differences between the first and the second half were significant, however, only for electrodes Cz ($t(83) = 4.98$, $p < .001$) and Pz ($t(83) = 4.05$, $p < .001$), whereas no significant differences were found at frontal sites (Fz: $p = .152$). Please see figure

S2 for a graphical illustration. All other results (not including the factor Learning Half) are detailed in the main manuscript.

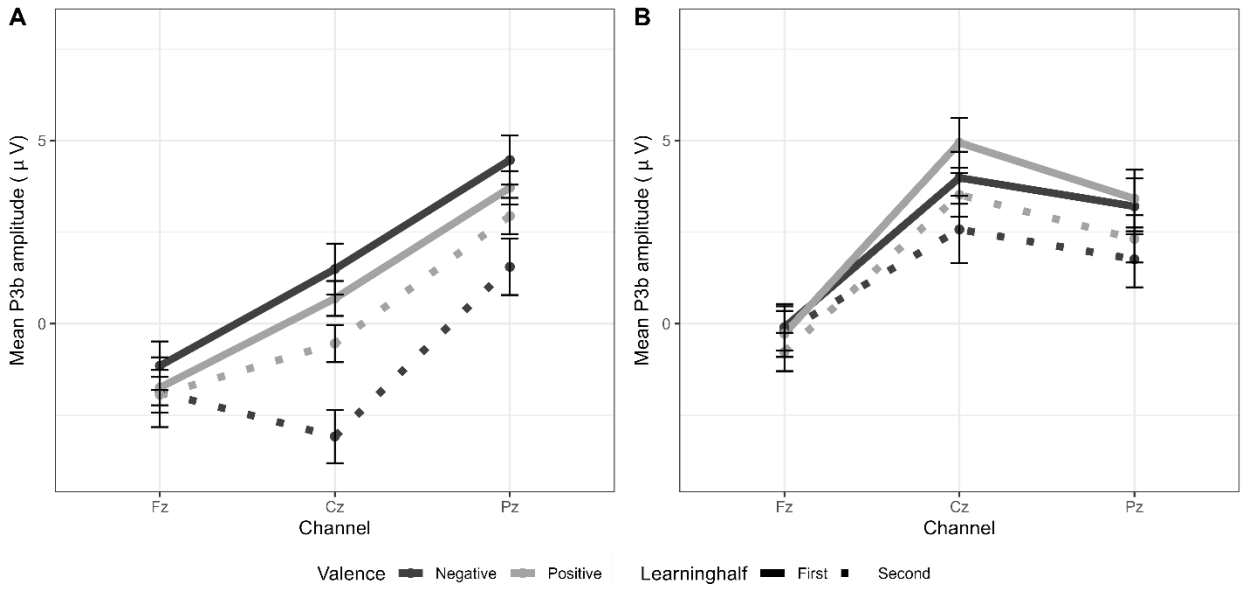


Figure S2. *Graphical illustration for the exploratory mean P3b analysis resolving the four-way interaction for A) the easy and b) the difficult group.*

9.2 Study 3: Supplementary Material

Feedback Stimuli Ratings

Objective With the following rating, we aimed to identify two pairs of social and non-social objects that were most comparable to each other in terms of stimulus characteristics such as visual complexity and familiarity with the objects. Furthermore, we wanted to assess whether both stimuli in a pair would elicit comparable affective and arousal responses. Identifying those stimulus pairs for which the social and non-social objects are most comparable to each other, will make the comparison of social and non-social feedback stimuli more reliable.

Participants and Procedure A total of 70 volunteers participated in an online rating study conducted in 2018. The online questionnaire was conducted via www.soscisurvey.de and available in English, German, and Mandarin. Participants were recruited via social media and word-of-mouth by the author DMP. The demographic details of the sample were:

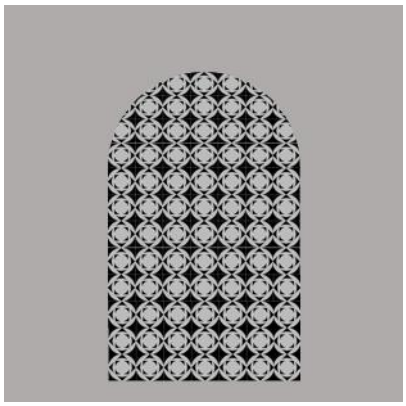
- Mean age: 33.5 years (SD = 10.1; range = 18–66)
- Sex distribution: 46 women, 24 men
- Language used for rating:
- German: 28 participants
- Mandarin: 38 participants
- English: 4 participants

Stimuli and pairs Six pairs of stimuli were created (twelve stimuli in total). Each pair consisted of a non-social and a social object which were rather similar in visual shape. Three stimulus pairs comprised 1-hand gestures as social objects and visually matching shapes, filled with a geometric pattern, as non-social objects. The three other stimulus pairs comprised 2-hand gestures as social objects and visually matching shapes as non-social objects.

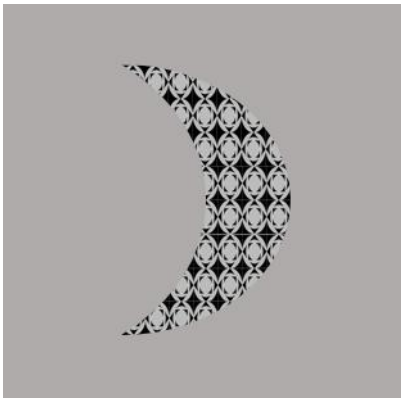
The sequence of the twelve stimuli was separately randomized for each participant. Participants evaluated each stimulus along four dimensions using 7-point Likert scales:

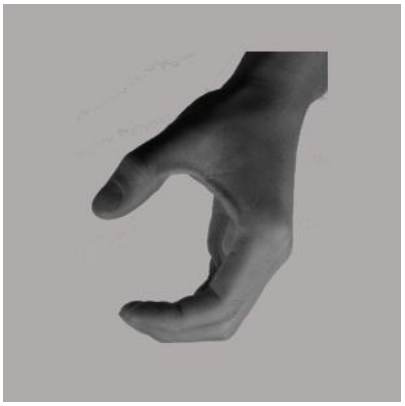
- Visual complexity (1 = very simple; 7 = very complex)
- Valence (1 = very negative; 7 = very positive)
- Familiarity (1 = unfamiliar; 7 = very familiar)
- Arousal (1 = very calm; 7 = very exciting)

Pair 1:

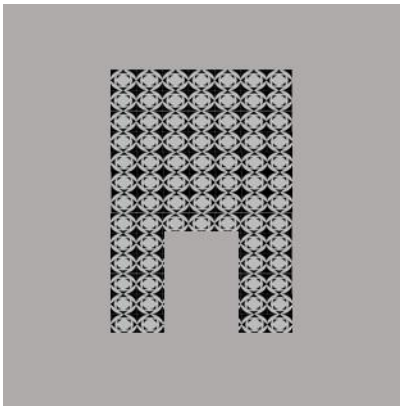


Pair 2:

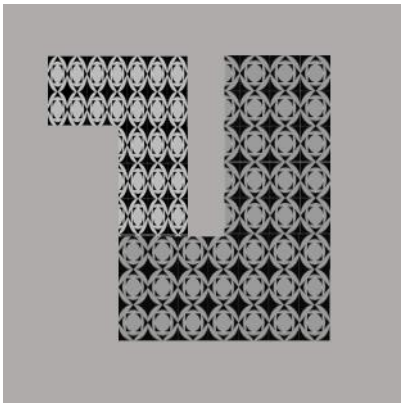




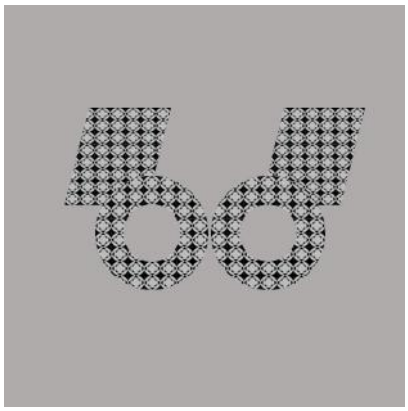
Pair 3:



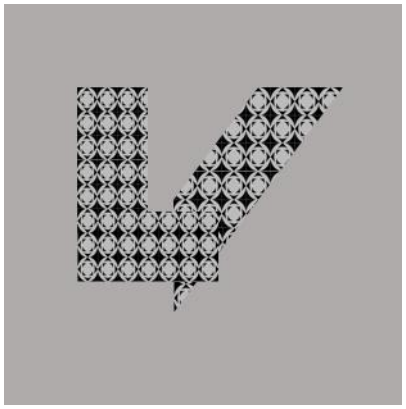
Pair 4:



Pair 5:



Pair 6:



Statistical Analysis First, each stimulus pair was evaluated separately, i.e., comparing the social and the non-social object. Main comparisons were conducted using Kruskal-Wallis tests, because the rating data were not normally distributed. Paired t-tests were additionally conducted and yielded comparable results.

Pairwise Comparison Results

Table S1.Pairwise comparisons of social vs. non-social stimuli across complexity, valence, familiarity, and arousal

Pair	Complexity	Valence	Familiarity	Arousal
1	p < .001, NS > S	ns (p = .594)	p < .001, NS < S	p < .001, NS < S
2	p = .004, NS > S	p = .036, NS > S	ns (p = .227)	ns (p = .060)
3	p = .033, NS > S	p = .045, NS > S	p < .001, NS < S	ns (p = .992)
4	ns (p = .285)	ns (p > .999)	p = .003, NS < S	ns (p = .271)
5	p < .001, NS > S	p = .031, NS < S	p < .001, NS < S	ns (p = .831)
6	p < .001, NS > S	ns (p = .190)	p < .001, NS < S	ns (p = .127)

Abbreviations: NS = Non-social stimulus; S = Social stimulus; ns = not significant

Summary of Stimuli Comparisons Arousal: All pairs usable because of non-significant differences except Pair 1, Valence: Pairs 1, 4, 6 preferred because of non-significant differences, Visual complexity: Only Pair 4 shows no significant differences, for all other pairs complexity is rated higher for non-social than social stimuli, Familiarity: Only Pair 2 shows no significant difference; for all the other pairs familiarity is rated higher for social than non-social stimuli.

Justification of Stimulus Choice: Based on the results above, Pairs 4 and 6 - both consisting of two hands or two objects - showed the least significant differences in the four assessed characteristics. To further corroborate this choice, we conducted repeated-measures ANOVAs with the ratings of Pairs 4 and 6 for each characteristic to directly compare the stimuli.

Repeated-measures ANOVA of Pairs 4 & 6: Visual complexity: The 2x2 ANOVA model testing for complexity showed significant main effects for Feedback Type (F(1,69)=4.06, p=.048, η_p^2 =0.06) and Stimulus Pair (F(1,69)=29.90, p<.001, η_p^2 =0.30), and a significant interaction effect of both factors (F(1,69)=23.09, p<.001, η_p^2 =0.25). Tukey post-hoc tests showed that complexity ratings did not differ for non-social stimuli of both pairs (p=.998), while the complexity ratings for social stimuli of both pairs did - the social stimulus of pair 6 was rated less complex than the social stimulus of pair 4 (p<.001), and less complex than both non-social stimuli (p's<.001).

Valence: The 2x2 ANOVA model testing for valence did not show any significant results - Feedback Type (p=.379), Stimulus Pair (p=.444), interaction Feedback Type x Stimulus Pair (p=.340).

Arousal: The 2x2 ANOVA model testing for arousal showed a significant main effect of Stimulus Pair (F(1,69)=8.63, p=.004, η_p^2 =0.11) and a significant Feedback Type x Stimulus Pair interaction (F(1,69)=9.19, p=.003, η_p^2 =0.12), while the factor Feedback Type was not significant (p=.775). Tukey post-hoc tests showed that the interaction was driven by a significant difference in arousal ratings between the two social stimuli of pair 4 an 6 (p=.001). The social stimulus of pair 6 was rated as less arousing than the social stimulus of pair 4. No other comparisons were significiant (all p's>.100).

Familiarity: The 2x2 ANOVA model testing for familiarity showed significant main effects of Feedback Type (F(1,69)=41.47, p<.001, η_p^2 =0.38) and Stimulus Pair (F(1,69)=10.48, p=.002, η_p^2 =0.13), and a significant interaction effects of both factors (F(1,69)=9.50, p=.003, η_p^2 =0.12). Tukey post-hoc tests showed no differences in familiarity for both non-social stimuli (p=.987). Both social stimuli were rated more familiar than both non-social stimuli (all p's<.008). When comparing both social stimuli, the stimulus of pair 6 was rated higher than the one of pair 4 (p=.002).

Decision We decided to use Pair 4 and Pair 6 for the experiment, because these two pairs did have the least differences between social and non-social ratings. Some differences were unfortunately not avoidable, as social stimuli may be inherently more familiar and arousing.

Table S2. Means and SD of the respective ratings for social and non-social stimuli of Pairs 4 and 6. All models were computed as 2 x 2 within-subject designs with factors Stimulus Pair (Levels: Pair 4/Pair 6) and Feedback Type (Social/Non-social).

		Complexity		Valence		Arousal		Familiarity	
		M	SD	M	SD	M	SD	M	SD
Social	pair4	4.93	1.32	3.80	0.91	4.30	1.26	3.10	1.59
	pair6	3.70	1.47	3.97	1.03	3.61	1.32	4.01	1.63
Non-social	pair4	4.69	1.42	3.80	0.91	3.90	1.61	2.39	1.27
	pair6	4.66	1.28	3.79	0.74	3.93	1.41	2.33	1.40