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Choosing with awareness: the role of feedback and metacognition in decision-making from a neuroscientific perspective

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Preface

This doctoral research stems from the intention to explore in depth the complex and multifaceted domain of Executive Functions (EFs), a central construct in contemporary cognitive psychology and neuroscience. In a world marked by increasing cognitive, emotional, and decision-related demands, understanding the mechanisms that govern goal-directed behavior is not only a theoretical pursuit but also a practical necessity.

Executive Functions have long been the subject of intense scientific debate. Despite decades of research, fundamental questions remain unresolved, including whether EFs represent a unitary or multidimensional construct, how they should be operationally defined, and what their precise neural correlates are. Through a critical review of both classical and modern theoretical frameworks – from the pioneering work of Luria and Lezak to recent neurocognitive and metacognitive perspectives – this dissertation aims to clarify the internal architecture of EFs, with particular focus on the interplay between cognitive, emotional, and motivational components.

Among these components, decision-making plays a particularly central role. Widely recognized as a core executive function, it embodies the dynamic integration of cognitive control, emotional processing, and contextual adaptation. This project investigates how feedback and metacognitive monitoring influence decision-making across different experimental paradigms, drawing on neurophysiological measures – notably electroencephalography (EEG) – to uncover the underlying mechanisms that support adaptive behavior.

By integrating theory and empirical evidence, this work seeks to provide both a conceptual contribution to the field and a foundation for future applied research in contexts such as education, clinical intervention, and organizational development, where the enhancement of executive functioning can promote autonomy, cognitive flexibility, and strategic self-regulation.

Chapter 1 – Introduction

1.1 Executive Functions: theoretical perspectives and recent advances

In recent decades, Executive Functions (EFs) have emerged as a core construct within neuropsychology and cognitive neuroscience. Despite the growing body of research, findings have often been inconsistent, contributing to an ongoing debate regarding the fundamental characteristics of these abilities. Although widely referenced in the literature, EFs still lack a universally accepted definition (Jurado & Rosselli, 2007) underscoring the multifaceted and conceptually complex nature of the construct (Silva et al., 2024)

Specifically, different recent reviews have tried to identify and analyze studies and definitions related to EFs (Dias et al., 2023; Goldstein et al., 2013; Silva et al., 2024) , highlighting how no single definition clearly and ultimately encompasses such cognitive function. For instance, Goldstain et al. (2013) identified a total of 33 distinct definitions of EFs (see Table 1), whereas a recent review by Dias et al. (2023) underscored how out of the 242 articles analyzed, 184 (76%) lacked an explicit definition of EFs.

Notably, a search conducted in the APA PsycInfo database Baggetta & Alexander (2016) revealed that one of the main points of agreement among the reviewed studies is that EFs are a multidimensional construct, as noted in 79% of the research. However, there were notable differences across the studies, including the use of 48 distinct models, the identification of 39 different EFs components (with the most commonly mentioned being inhibitory control/response inhibition, working memory/updating, and shifting/cognitive flexibility/switching), and a wide variety of assessment tools – comprising 11 batteries/scales and 109 different tests or tasks (Dias et al., 2023).

Despite the ongoing challenges in establishing consensus regarding the models and components of EFs, a commonly accepted definition conceptualizes EFs as a set of higher-order, multidimensional cognitive processes responsible for the regulation and direction of behavior (Baggetta & Alexander, 2016; Dias et al., 2023). As such, EFs are often described as an overarching construct that encompasses a broad array of cognitive and behavioral skills (Chan et al., 2008) , as well as their support role in learning, socioemotional competence, and everyday functioning (Baggetta & Alexander, 2016; Diamond, 2013) , contributing to the development of autonomy and productive engagement in daily activities (Zelazo, 2020) .

Interestingly, the analysis of EFs definitions further revealed that over 90% of the studies conceptualized EFs as a multidimensional construct (Dias et al., 2023) . Indeed, another major debate within the literature concerns the existence of a unified executive factor versus the presence of distinct, dissociable EFs, reflecting the tension between unity and diversity in the conceptualization of executive functioning (Silva et al., 2024) . Specifically, several theoretical models have proposed a unified EF, suggesting a single cognitive system underlying executive control. Notable examples include Norman and Shallice's (1986) Supervisory Attentional System (SAS), Baddeley and Hitch's (1974) central executive in the working memory model, Posner and Snyder's (1975) cognitive control model, Goldman-Rakic's (1995) unitary executive framework, Grafman's (2002) structured event model, Engle's (2002) executive attention theory, and Braver's (2012) dual mechanisms framework. Recent cognitive neuroscience models also support this unitary perspective, often associating EFs with frontal lobe activity. However, subsequent revisions of these models acknowledge the potential fractionation of EFs into distinct components, thus aligning with a more multidimensional view (Silva et al., 2024).

Indeed, contrary to unitary models, numerous theories conceptualize EFs as a set of distinct but interrelated processes. These include Fuster's hierarchical frontal lobe model (1993) , Zelazo and Frye's (1998) cognitive complexity theory, Stuss and Alexander's (2000) model of multiple attentional systems, Duncan's (2010) multiple-demand system, Lezak et al.'s (1982) neuropsychological framework, and psychometric models identifying between two and five distinct executive factors (Karr et al., 2018) . As the general concept of executive functioning has been further differentiated, core components have been identified, such as planning, decision-making, emotional and impulse control, reasoning, sustained attention, verbal fluency, response inhibition, cognitive flexibility, dual-tasking, and various aspects of working memory (e.g., maintenance, monitoring, and updating).

McCloskey, Perkins, and Van Divner (2011) offered an operational definition of EFs based on six interrelated principles:

1. EFs are diverse in nature; they do not represent a single, unified trait.

2. EFs are directive in nature, meaning they are mental constructs that guide and coordinate the use of other mental processes.

3. EFs direct mental activity differently across four major domains: perception, emotion, cognition, and action.

4. The application of EFs can vary widely across four contexts: intrapersonal, interpersonal, environmental, and symbolic system use.

5. EFs begin developing early in childhood and continue maturing at least into the third decade of life, likely evolving throughout the lifespan.

6. The use of EFs is reflected in the activation of neural networks within various regions of the frontal lobes.

In the context of the current work, we describe EFs as an umbrella term that refers to a set of top-down, high-level mental processes that promote actions directed toward goal attainment, that essentially operate as a metacognitive, supervisory, controlling system (Balconi et al., 2020; Diamond, 2013; Miller & Cohen, 2001; Ward, 2019) encompassing several cognitive functions, including but not limited to working memory, inhibition, self-regulation, cognitive flexibility, decision-making, problem solving, reasoning, and planning. Nevertheless, to provide a clearer understanding of the construct of EFs, we will present a brief historical overview outlining the major theoretical models developed over time.

Table 1. Review of EFs definitions (adapted from Goldstein et al., 2014).

Authors	Definition
Anderson (2002)	Processes associated with EF are numerous, but the principal elements include anticipation, goal selection, planning, initiation of activity, self-regulation, mental flexibility, deployment of attention, and utilization of feedback.
Banich (2009)	Providing resistance to information that is distracting or task irrelevant, switching behavior task goals, utilizing relevant information in support of decision making, categorizing or otherwise abstracting common elements across items, and handling novel information or situations.
Barkley (2011)	EF is thus a self-directed set of actions intended to alter a delayed (future) outcome (attain a goal for instance).
Baron (2004)	Executive functioning skills allow an individual to perceive stimuli from his or her environment, respond adaptively, flexibly change direction, anticipate future goals, consider consequences, and respond in an integrated or commonsense way.
Best et al. (2009)	Executive function (EF) serves as an umbrella term to encompass the goal-oriented control functions of the PFC.
Borkowski and Burke (1996)	EF coordinates two levels of cognition by monitoring and controlling the use of the knowledge and strategies in concordance with the metacognitive level.
Burgess (1997)	A range of poorly defined processes which are putatively involved in activities such as problem-solving, … planning … 'initiation' of activity, 'cognitive estimation,' and 'prospective memory.'
Corbett et al. (2009)	Executive function (EF) is an overarching term that refers to mental control processes that enable physical, cognitive, and emotional self-control.
Crone (2009)	For example, during childhood and adolescence, children gain increasing capacity for inhibition and mental flexibility, as is evident from, for example, improvements in the ability to switch back and forth between multiple tasks.
Dawson and Guare (2010)	Executive skills allow us to organize our behavior over time and override immediate demands in favor of longer-term goals.
Delis (2012)	Executive functions reflect the ability to manage and regulate one's behavior in order to achieve desired goals.
Delis (2012)	Neither a single ability nor a comprehensive definition fully captures the conceptual scope of executive functions; rather, executive functioning is the sum product of a collection of higher level skills that converge to enable an individual to adapt and thrive in complex psychosocial environments.
Denckla (1996)	EF has become a useful shorthand phrase for a set of domain-general control processes….
Friedman et al. (2007)	… a family of cognitive control processes that operate on lower-level processes to regulate and shape behavior.
Funahashi (2001)	Executive function is considered to be a product of the coordinated operation of various processes to accomplish a particular goal in a flexible manner.
Fuster (1997)	EF …is closely related, if not identical, to the function of temporal synthesis of action, which rests on the same subordinate functions. Temporal synthesis, however, does not need a central executive.
Gioia et al. (2000)	The executive functions are a collection of processes that are responsible for guiding, directing, and managing cognitive, emotional, and behavioral functions, particularly during active, novel problem solving.
Gioia and Isquith (2004)	The executive functions serve as an integrative directive system exerting regulatory control over the basic, domain-specific neuropsychological functions (e.g., language, visuospatial functions, memory, emotional experience, motor skills) in the service of reaching an intended goal.

Authors	Definition
Hughes (2009)	The term executive function (EF), therefore, refers to a complex cognitive construct encompassing the whole set of processes underlying these controlled goal-directed responses to novel or difficult situations, processes which are generally associated with the prefrontal cortex (PFC).
Lezak (1995)	Executive functioning asks how and whether a person goes about doing something.
Lezak (1995)	Executive functions refer to a collection of interrelated cognitive and behavioral skills that are responsible for purposeful, goal-directed activity, and include the highest level of human functioning, such as intellect, thought, self-control, and social interaction.
Luria (1966)	…Syntheses underlying own actions, without which goal-directed, selective behavior is impossible.
Luria (1966)	…besides the disturbance of initiative and the other aforementioned behavioral disturbances, almost all patients with a lesion of the frontal lobes have a marked loss of their 'critical faculty,' i.e., a disturbance of their ability to correctly evaluate their own behavior and the adequacy of their actions.
McCloskey (2011)	It is helpful to think of executive functions as a set of independent but coordinated processes rather than a single trait.
McCloskey (2006)	Executive Functions can be thought of as a diverse group of highly specific cognitive processes collected together to direct cognition, emotion, and motor activity, including mental functions associated with the ability to engage in purposeful, organized, strategic, self-regulated, goal directed behavior.
Miller and Cohen (2001)	[our theory] suggests that executive control involves the active maintenance of a particular type of information: The goals and rules of a task.
Oosterlaan, et al. (2005)	EF encompasses meta-cognitive processes that enable efficient planning, execution, verification, and regulation of goal directed behavior.
Pribram (1973)	… the frontal cortex is critically involved in implementing executive programmes where these are necessary to maintain brain organization in the face of insufficient redundancy in input processing and in the outcomes of behavior.
Robbins (1996)	Executive function is required when effective new plans of action must be formulated, and appropriate sequences of responses must be selected and scheduled.
Roberts and Pennington (1996)	EF refers to a collection of related but somewhat distinct abilities such as planning, set maintenance, impulse control, working memory, and attentional control.
Stuss and Benson (1986)	Executive functions is a generic term that refers to a variety of different capacities that enable purposeful, goal-directed behavior, including behavioral regulation, working memory, planning and organizational skills, and self-monitoring.
Vriezen and Pigott (2002)	Executive function has been defined in a variety of ways but is generally viewed as a multidimensional construct encapsulating higher-order cognitive processes that control and regulate a variety of cognitive, emotional and behavioral functions.
Welsh and Pennington (1988)	Executive function is defined as the ability to maintain an appropriate problem-solving set for attainment of a future goal.

1.1.1 Classical theories of Executive Functions

1.1.1.1 From Luria to Lezak

Before describing some of the milestone theories of EFs, it is essential to mention the model of Luria derived from his studies of individuals with frontal lobe damage. He was the first to observe that they exhibited disorganized behavior and ineffective strategies when performing everyday tasks, and therefore developed a theory of brain functioning known as the *Three Functional Units* (Luria, 1973), which assigns distinct cognitive roles to specific brain regions. The first unit, responsible for arousal and motivation, involves the limbic and reticular systems and is situated in the brainstem, governing alertness and arousal. The second unit, encompassing the post-rolandic cortical areas – including the temporal, occipital, and parietal lobes – is involved in receiving, processing, encoding, and storing information. The third unit, which Luria emphasizes as having an executive role, is located in the frontal lobes and is responsible for programming, controlling, regulating, and verifying human behavior. These early studies laid the foundation for the development of theoretical models of executive function, and these findings can be interpreted as supporting the idea of EFs as a unified construct, attributing the frontal lobes as the central region responsible for all behavioral regulation (Silva et al., 2024).

Keeping up from such premises, Norman and Shallice conducted research to investigate the functions of the frontal lobes and their role in regulating human behavior, aiming to expand knowledge about the contribution of these brain areas to cognition and attentional control (Silva et al., 2024) . Their aim was to shed light on the mechanisms underlying executive control, especially in situations requiring conscious decision-making rather than automatic responses (Goldstein et al., 2013). In 1986, they developed a theoretical model known as the *Supervisory Attentional System* (SAS), which describes attention as operating through two systems: the preprogrammed system, responsible for habitual and automatic actions, and the SAS, which functions at a more controlled level to manage novel or complex situations (Norman & Shallice, 1986). The SAS regulates attention, inhibits perseverative behaviors, suppresses responses to irrelevant stimuli, and generates new actions in unfamiliar contexts. The level of control attributed to the SAS by Norman and Shallice was interpreted as evidence of the unity of EFs, as they proposed that all attentional control processes were managed by a single system. According to Shallice, when this system is impaired or dysfunctional, individuals may experience executive function deficits, such as difficulties with inhibition or self-regulation, manifesting in behaviors like impulsivity or disinhibition (Shallice, 2002) . These impairments highlight the essential role of the SAS in adaptive, goal-directed behavior.

Later, the SAS model inspired an updating and revision of Baddeley & Hitch (1974) model of working memory functioning: indeed, they postulated the existence of the central executive as a control system coordinating and overseeing the phonological loop (for verbal information) and the visuospatial sketchpad (for visual data) and is primarily associated with the frontal lobes (Baddeley, 1996) .

At first, the central executive was thought to operate as a unified system responsible for overseeing all aspects of information processing and cognitive control, functioning as a general attentional resource. However, as research progressed, particularly through experimental studies, Baddeley and Hitch identified that the central executive is composed of multiple distinct functions. These include managing two tasks simultaneously (dual-task performance), focusing attention selectively, switching between tasks, and activating information stored in long-term memory (Baddeley, 1996; Baddeley et al., 2020) .

Building on the idea that EFs do not represent a single, unified process but are instead composed of multiple distinct yet interrelated processes, various frameworks have been proposed to explain this complexity. For example, Lezak et al. (2004) proposed a four-component model of EFs that highlights the cognitive abilities required for independent, goal-directed, and adaptive behavior. These include volition, the capacity to plan and make decisions, the initiation of purposeful actions, and the ability to carry out those actions effectively. This model underscores the multifaceted and functional nature of executive processes, especially in real-world contexts.

1.1.2 Modern perspectives on Executive Functions

1.1.2.1 The unity and diversity model of executive functions

In line with this view, in the 2000s, several models were proposed that described EFs as a multicomponent factor. Among these, the most popular and influential model is probably the *Unity and Diversity Model of Executive Functions* by Miyake et al. (2000) which advanced a theoretically and empirically grounded model of executive functions that underscores both their integrative and dissociable nature. Through latent variable analysis, the authors identified three core components – *shifting* (the ability to alternate between tasks or mental sets), *updating* (the continuous monitoring and revision of working memory representations), and *inhibition* (the deliberate suppression of dominant or automatic responses) – demonstrating that while these functions are moderately intercorrelated, they remain functionally distinct. This evidence supports a conceptualization of executive functioning as a set of related but separable cognitive processes, each contributing differentially to complex goal-directed behavior and higher-order cognitive tasks.

Although the set of executive functions identified by Miyake et al. (2000) was not intended to be exhaustive, their selection was guided by both practical considerations and neuroanatomical evidence, as each of the three core functions – shifting, updating, and inhibition – has been linked to distinct regions of the neocortex. This targeted approach allowed for the investigation of executive processes that are both theoretically meaningful and empirically measurable, while maintaining relevance to known neural substrates (Löffler et al., 2024).

1.1.2.2 Guided Activation Theory

Similarly, Miller and Cohen (2001) proposed a comprehensive model of prefrontal cortex (PFC) function known as the *Guided Activation Theory*, which conceptualizes executive functioning as a form of cognitive control rooted in the active maintenance of goal-relevant representations. In their framework, EFs are understood as a top-down system that facilitates coordinated behavior by biasing the activity of sensory, cognitive, and motor systems toward goal-directed outcomes. The PFC achieves this by generating bias signals that shape the flow of neural activity along task-relevant pathways, thereby establishing appropriate mappings between stimuli, internal states, and responses. These pathways function as dynamic "maps" linking inputs to outputs, allowing the organism to override habitual responses in favor of context-appropriate behavior. Executive functioning, in this model, serves as an umbrella term encompassing a range of cognitive processes that support purposeful behavior, especially in situations requiring flexibility, inhibition, and sustained attention. The model is grounded in evidence from neurophysiology, neuroimaging, and computational modeling, and positions the PFC as a modulatory hub essential for the integration and regulation of complex, goal-directed actions.

1.1.2.3 Diamond model of Executive Functions

Starting from Miyake et al.'s model (2000) , Diamond (2013) postulated a model where EFs are conceptualized as a set of interrelated top-down cognitive processes essential for purposeful, goal-directed behavior. These functions are indispensable for the execution of goal-oriented activities, adaptive problem-solving, and flexible adjustment to dynamic environmental demands (Figure 1). The three principal components of executive functioning include:

- *Inhibitory control*, which enables individuals to suppress automatic responses, resist external distractions, and override impulsive tendencies;
- *Working memory*, which allows for the temporary maintenance and manipulation of information essential for reasoning and learning;
- *Cognitive flexibility*, which underlies the capacity to shift perspectives, alternate between tasks, and adapt strategies in response to changing circumstances.

These core functions serve as the scaffolding for more complex executive processes, such as strategic planning, abstract reasoning, problem resolution, and emotional self-regulation – all of which are critical to academic performance, occupational competence, social functioning, and psychological well-being.

Diamond (2013) highlights that contextual and psychological variables – including chronic stress, insufficient sleep, emotional dysregulation, and social disconnection – can substantially compromise executive functioning. Given that EFs are heavily dependent on the integrity of the prefrontal cortex, they are particularly susceptible to such adverse influences. Accordingly, they are often regarded as a neurocognitive sentinel, or a "*canary in the coal mine*," signaling emerging disruptions in cognitive and emotional health.

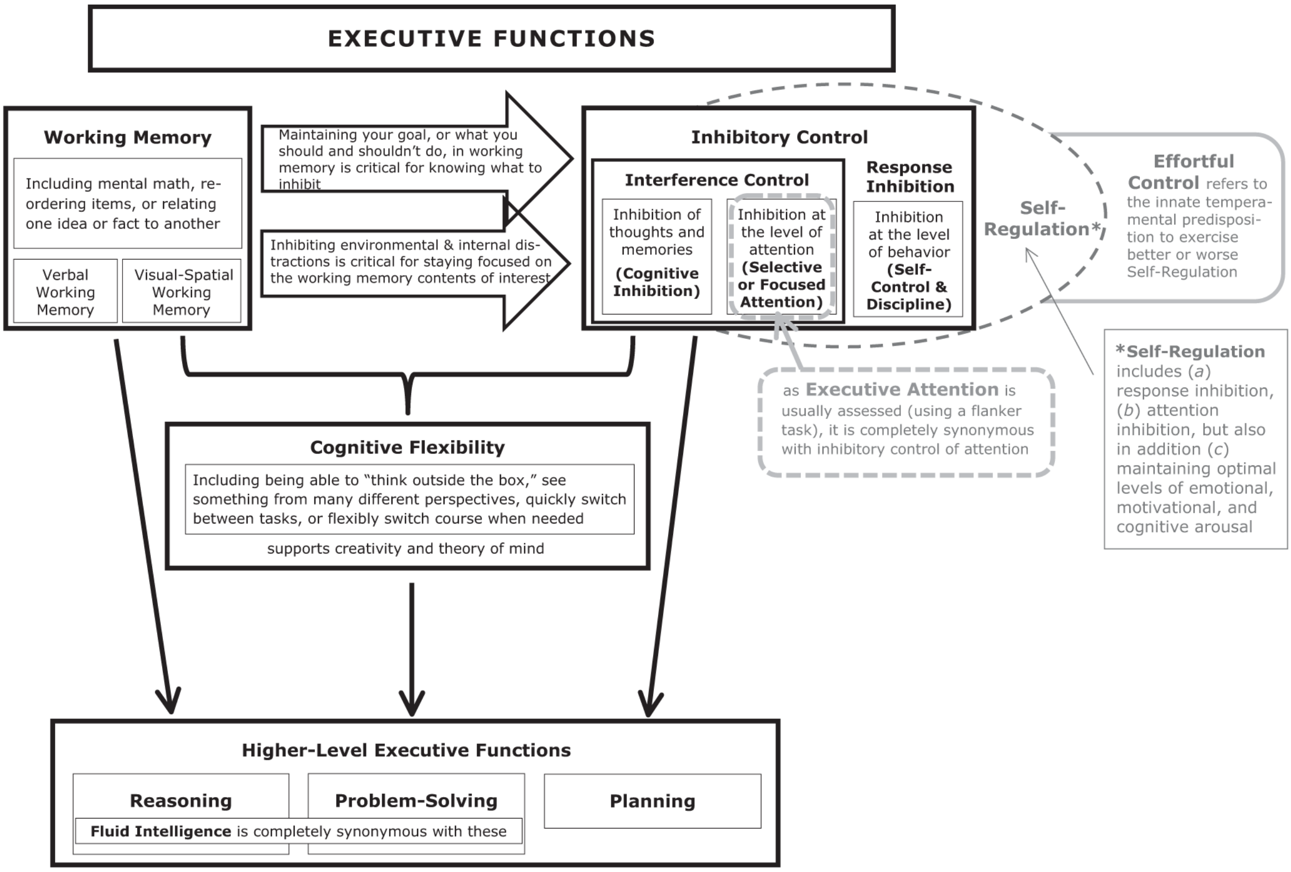

Figure 1. Diamond conceptualisation of EFs (from Diamond, 2013).

Multiple studies have validated this three-factor structure of EFs – namely, inhibition, working memory/updating, and cognitive flexibility/shifting – particularly in adult populations, as confirmed by systematic reviews and meta-analyses (Ustárroz et al., 2017). Although some research has identified additional factors, such as verbal fluency or decision-making (Ustárroz et al., 2017), the predominance of evidence supporting these three domains may have contributed to an overemphasis on them. As a result, these components have sometimes been treated as the "*Holy Trinity*", virtually synonymous with the broader concept of executive functioning, potentially overshadowing other important aspects or more clinically grounded models (Dias et al., 2023).

1.1.2.4 "Hot" and "cold" model of Executive Functions

In neuropsychology, hierarchical and multicomponent models offer three main contributions: (1) they help distinguish complex behaviors like planning and cognitive flexibility from simple automatic responses; (2) they allow for the development of tasks to assess individual cognitive components, aiding diagnosis and treatment of brain-injured patients; (3) they provide a broader understanding of how executive dysfunction impacts behavior beyond isolated cognitive deficits (Kluwe-Schiavon et al., 2017) . However, these models still rely on the traditional framework of "cognitive control," where the PFC regulates goal-directed behavior and emotional self-regulation. To better explain these control mechanisms, researchers have turned to dual-process theories, which differentiate between "cold" and "hot" cognitive systems (Zelazo & Carlson, 2012), emphasizing the role of emotional and motivational context in cognitive control (Figure 2). Specifically:

(i) *hot* EFs are engaged in emotionally salient or motivationally charged situations and are associated with the orbitofrontal cortex and related medial brain structures; they encompass the handling of information associated with reward, emotion, and motivation, including emotion regulation, reward processing, delay discounting, decision-making and affective decision;

(ii) *cold* EFs refers to the deliberate, top-down regulation of behavior in affectively neutral situations, involving purely cognitive processes, including working memory, response inhibition, attentional control and problem solving (involving dorsolateral regions of the PFC).

While cold EFs typically emerge and develop rapidly during early childhood, hot EFs appear to follow a more protracted developmental trajectory, becoming more refined during adolescence.

Neuropsychological and neuroimaging evidence supports a partial dissociation between the two systems, with lesion studies indicating that impairments in one system do not necessarily affect the other. Importantly, both components of EFs exhibit significant plasticity and can be enhanced through targeted interventions, especially during sensitive developmental windows such as early childhood and the transition to adolescence. Therefore, the differentiation between hot and cool EFs is supported by extensive experimental, clinical, and neurophysiological evidence, and it is currently acknowledged that cool EFs moderate the influence of hot EFs (Balconi & Crivelli, 2021; Rovelli & Allegretta, 2023).

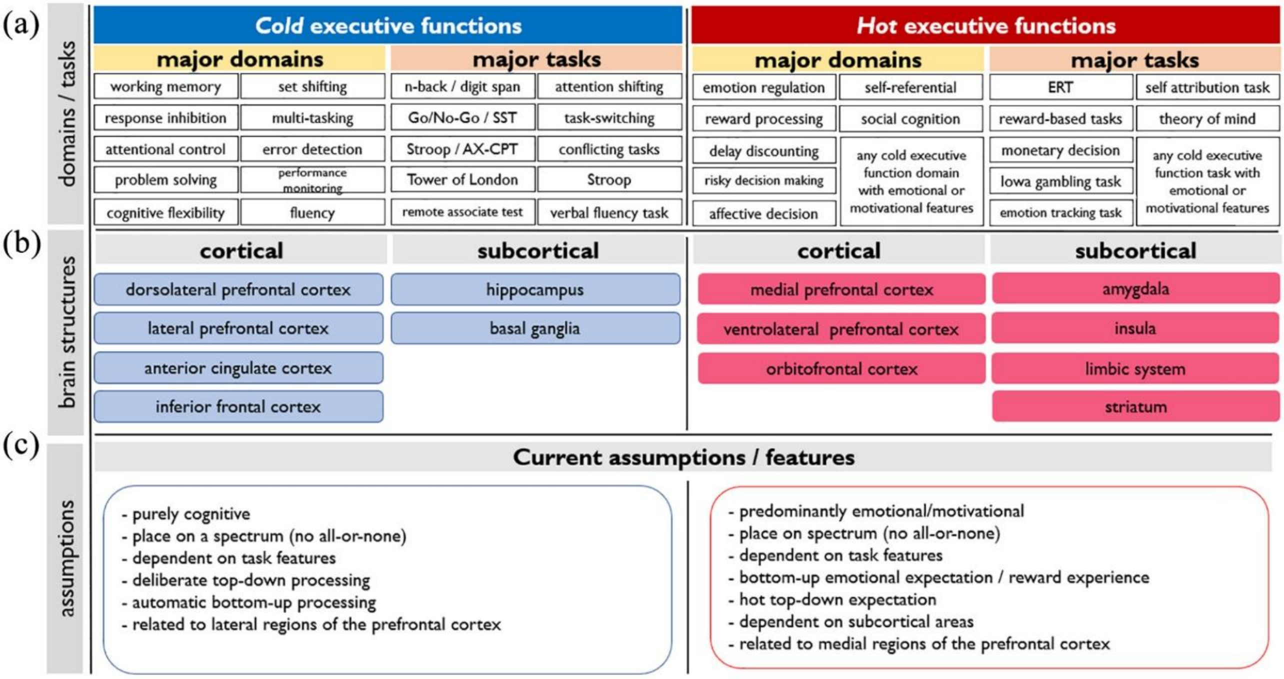

Figure 2. Differences between hot and cold executive functions across three key dimensions: (a) the types of domains and behavioral tasks used to assess them, (b) the specific brain regions involved, and (c) the core theoretical assumptions and defining characteristics associated with each (from Salehinejad et al.., 2021).

1.1.2.5 The Neuro-Empowerment Model of Executive Functions

In applied contexts, a particularly innovative and recent contribution to the modelling of EFs has been offered by Balconi et al. (2020) , who introduced the concept of neuro-empowerment to explain how executive functioning can be actively supported and enhanced in high-demand, real-life contexts such as organizational settings. Their model “*The Triadic Model for Assessment and Neuroempowerment*”

(Figure 3) conceptualizes EFs not as fixed cognitive traits, but rather as dynamic, trainable systems modulated by the interplay between neurocognitive activation, emotional self-regulation, and contextual complexity. The model organizes competencies into three interconnected domains:

(i) *Technical-Analytical Skills*: these include both task-specific and general cognitive abilities. Technical skills are tied to specific roles or disciplines and depend on education and experience (e.g., logical problem-solving). In contrast, analytical skills are more general and relevant across contexts, such as attention control, working memory, and inhibition.

(ii) *Metacognitive Skills*: these higher-order processes are vital in complex environments. They involve self-awareness and the ability to regulate one's cognitive and emotional states. Skills such as strategic planning, adaptive decision-making, self-evaluation, and intrinsic motivation fall under this category.

(iii) *Relational Skills*: essential in organizational settings, these encompass emotional and cognitive empathy, social awareness, and effective interpersonal interaction. They are central to emotional intelligence and support social and professional success.

While EFs, including inhibition, working memory, processing speed, and flexibility, are not isolated components in this model, they operate across and within all three domains, reflecting their integrative and regulatory role in supporting adaptive behavior. Within this perspective, EFs are embedded in a neurofunctional framework that emphasizes the role of prefrontal activation (especially frontal asymmetries and theta oscillations) as key biomarkers of adaptive control processes, which can be enhanced through feedback-based interventions and targeted cognitive training (Balconi et al., 2020).

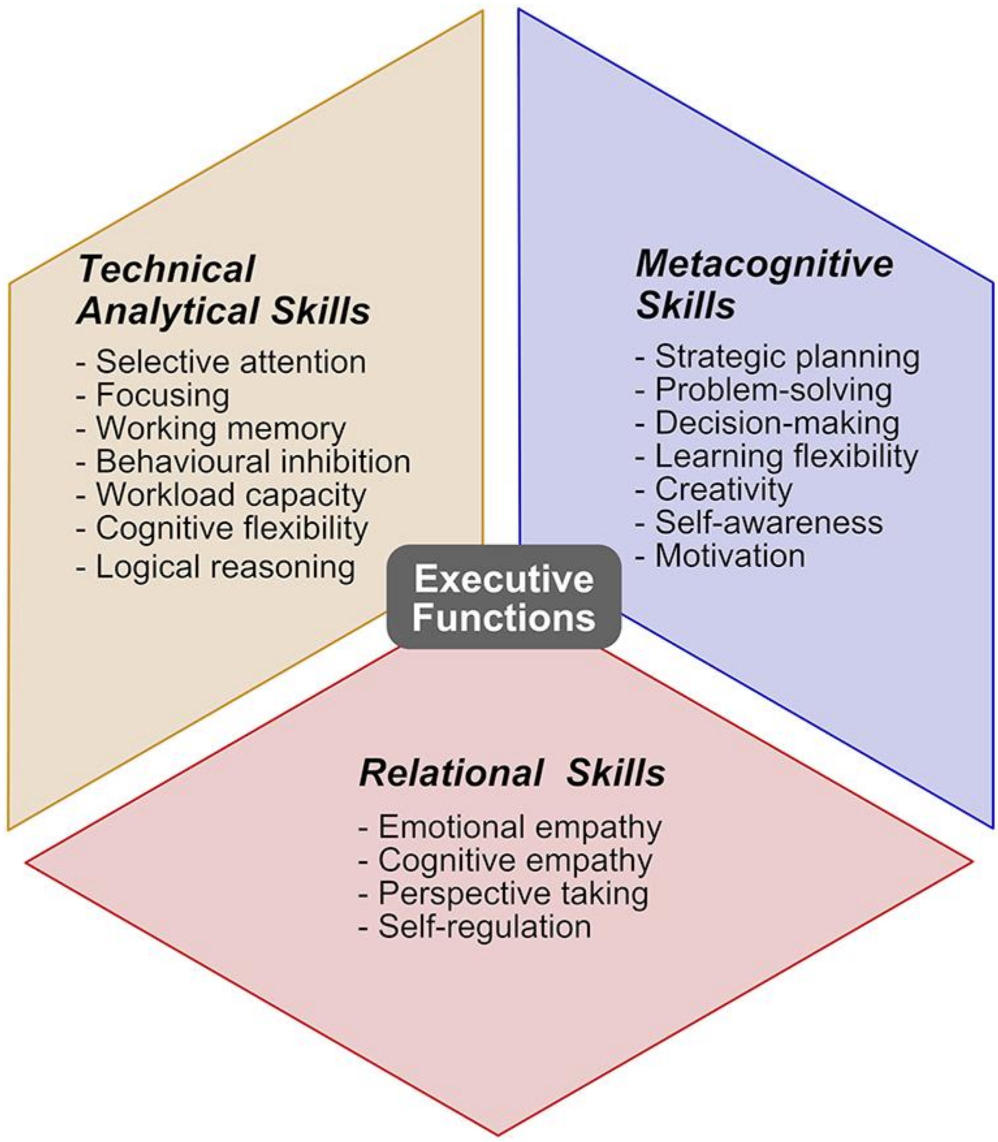

Figure 3. The triadic model of neuroempowerment for the executive functions at the workplace (from Balconi et al., 2020).

Building on this foundation, later work by Balconi, Acconito et al. (2023, 2024) has further elaborated the role of metacognitive monitoring and emotional regulation in EFs performance, showing that individual variability in self-awareness and motivation can predict the effectiveness of executive control. These studies highlight the need to consider not only the cognitive architecture of EFs, but also its modulation by affective and motivational dimensions, particularly in socially and emotionally salient environments. This approach aligns with the hot/cold EFs distinction, recognizing that executive functioning is not a purely rational mechanism but one that operates under the influence of internal states and external pressures.

Overall, the neuro-empowerment framework and related research offer a multicomponential and ecologically grounded model of EFs that connects theoretical constructs with measurable neurophysiological indices and concrete intervention strategies. By integrating cognitive control, emotional awareness, and contextual adaptation, Balconi's work bridges traditional models of executive functioning with contemporary demands for flexible, real-world applications, and provides a valuable roadmap for the development of neuroscience-based cognitive enhancement programs.

1.2 Neural correlates of Executive Functions

Although, as mentioned in the previous paragraphs, there is no universally accepted definition of EFs, numerous studies have tried to explore their underlying neural and physiological mechanisms. Much of the research on the neural basis of executive functioning originates from early observations of individuals with damage to the frontal lobes (Jurado & Rosselli, 2007) . These clinical findings laid the foundation for identifying specific brain areas – particularly within the PFC – as being critically involved in executive processes such as planning, decision-making, and impulse control. Over time, advances in neuroimaging – with technology such as magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), positron emission tomography (PET) – and cognitive neuroscience have further deepened our understanding, highlighting the complex and distributed nature of the brain networks that support EFs, including frontal and posterior regions of the cerebral cortex, as well as subcortical regions (Chung et al., 2014) .

Indeed, it is essential to begin by acknowledging that no individual region of the brain operates in complete isolation. Instead, brain function is best understood as the result of complex, dynamic interactions among numerous neural circuits that connect diverse areas across the brain. This integrative network model highlights how cognitive processes, including EFs, emerge from the coordinated activity of multiple brain regions working together rather than from a single localized area (Otero & Barker, 2014).

Positioned at the front of the brain, the frontal lobes represent the largest portion of the brain, making up nearly one-third of the human hemisphere and their full maturation is linked to the development of advanced cognitive abilities and behavioral patterns that are typical of adulthood (Catani, 2019; Otero & Barker, 2014) . Within the frontal lobes are several key structures, including the primary motor cortex, premotor cortex, supplementary motor area, Broca’s area for speech production, frontal eye fields, and the PFC (Figure 4). The prefrontal cortex plays a central role in regulating cognitive control and is typically divided into three main regions: the dorsolateral prefrontal cortex (DLPFC), the medial frontal cortex (including the anterior cingulate), and the orbitofrontal cortex (OFC).

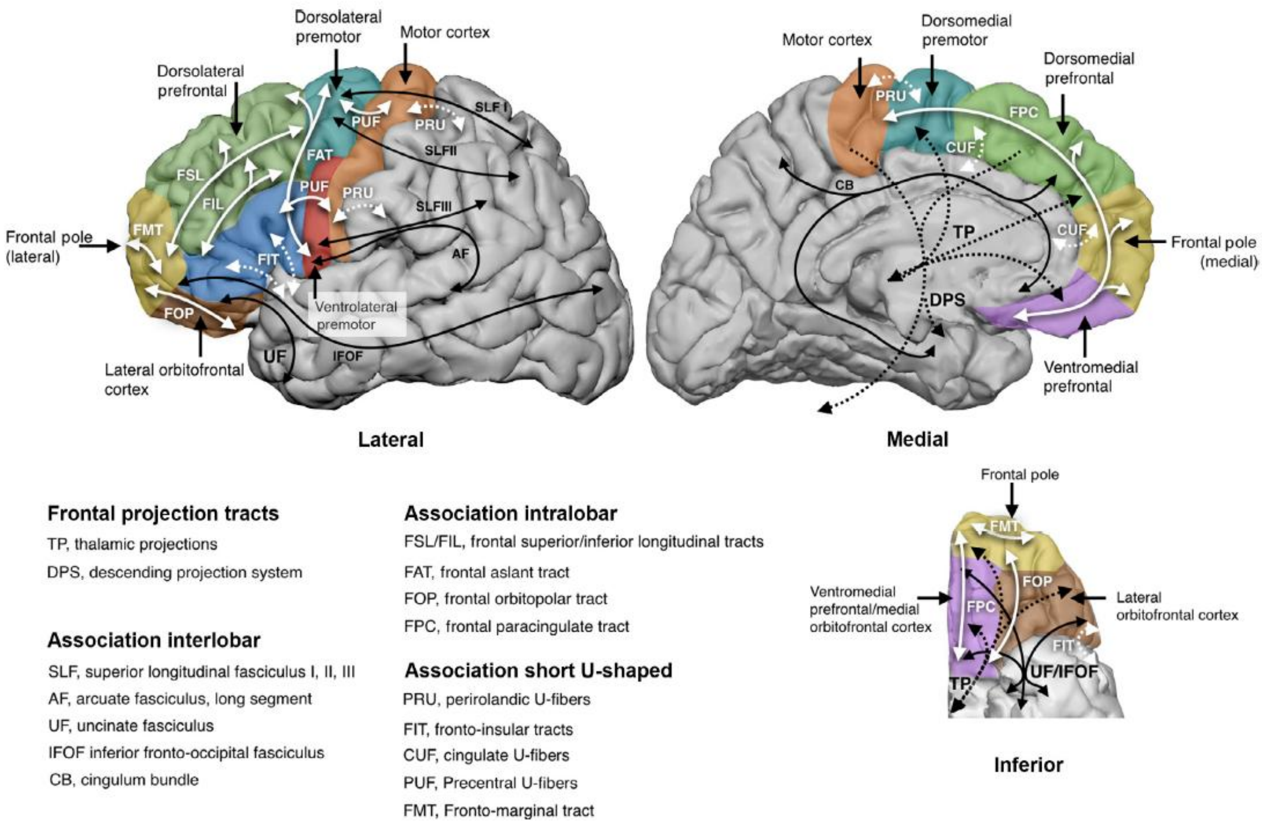

Figure 4. A diagram of the major regions within the frontal lobe illustrates their communication networks, including both association and projection pathways (from Catani, 2019).

The orbital and medial areas of the frontal lobe play a key role in regulating emotional behavior and are connected to both the brainstem and limbic system. In contrast, the lateral region – most highly developed in humans – is crucial for the cognitive processes that underpin the temporal structuring of behavior, language, and logical thinking. All of these regions participate in complex cortico-subcortical circuits, which include interactions with the basal ganglia and other brain areas.

As previously mentioned, in their conceptualization, a major debate in the field concerned the unity vs. non-unity of EFs; therefore, it is not surprising that such debate also permeated the study of its neural substrates. Interestingly, neuroimaging research highlights that the executive system is characterized by both unity and diversity. A study by Collette et al. (2005) using PET scans showed that different EFs – updating, shifting, and inhibition – activate shared brain areas, particularly in the parietal lobe (left superior parietal gyrus and right intraparietal sulcus), with some involvement of the left middle and inferior frontal gyri. However, each function also recruits distinct brain regions: updating engages both anterior and posterior regions bilaterally; shifting involves the parietal lobe and frontal gyri; and inhibition primarily activates the right orbitofrontal gyrus, though less specifically. These findings further suggest that EFs rely on a distributed neural network, with a significant role played by the parietal cortex, challenging the earlier view that they are localized mainly in the frontal lobes.

Nonetheless, some authors have proposed that there are two different, but closely related types of prefrontal lobe abilities associated with two different types of EFs: *metacognitive* EFs and *emotional/motivational* EFs (Ardila, 2008; Happaney et al., 2004) .

1.2.1 Metacognitive EFs

Metacognitive EFs refer to higher-order cognitive processes such as problem solving, abstract thinking, planning, creating and executing strategies, and working memory and are primarily mediated by the DLPFC (Ardila, 2008) . This area is extensively connected with both cortical and subcortical regions, enabling it to integrate and regulate information from multiple parts of the brain.

These connections include links to the thalamus, the dorsal part of the caudate nucleus within the basal ganglia, the hippocampus, and several associative areas of the neocortex, such as the posterior temporal, parietal, and occipital lobes.

Snellenberg & Wager (2009) proposed a hierarchical model of cognitive processing within the PFC, organized along an anterior-to-posterior gradient. This progression begins with the representation of stimulus value in the orbitofrontal and rostral medial prefrontal cortices. It continues with the encoding of internal goals and task hierarchies in the anterior insular and prefrontal regions, followed by top-down modulation of sensory processing in posterior cortices via the dorsolateral prefrontal cortex. Subsequently, specific stimulus-response mapping rules are maintained and updated in the inferior frontal junction and lateral premotor areas. The planning of goal-directed motor behavior is managed by the pre-supplementary motor area (pre-SMA) and cingulate motor regions, culminating in the execution of motor actions within the primary motor cortex (Snellenberg & Wager, 2009).

1.2.2 Emotional/motivational EFs

Emotional/motivational EFs refer to the capacity to integrate cognitive processes with emotional and motivational states. This involves regulating and directing basic impulses in ways that align with socially appropriate behavior. In this domain, the primary concern is not necessarily achieving the most intellectually or conceptually optimal outcome but rather acting in a manner consistent with one's internal drives and emotions while adhering to social norms (Ardila, 2008).

Emotional and motivational executive processes are primarily governed by the orbitofrontal and anterior cingulate/medial circuits, which facilitate the integration of emotion and cognition (Fuster, 1999). The OFC includes both ventral and medial areas of the PFC. As part of the frontostriatal system, it maintains strong connections with the amygdala and other limbic structures, supporting the coordination of emotional input with cognitive control and the regulation of goal-directed, motivated behavior (Chudasama & Robbins, 2006).

1.3 Decision-making: a core executive function

In the previous paragraphs, we have attempted to provide an overview of definitions and models of EFs (see Section 1.1) to highlight not only the difficulty of reaching a consensus on a single, yet fundamental, construct in cognitive psychology, neuropsychology and neuroscience, but also the pervasive and essential role of EFs in every aspect of life.

Therefore, given their central role in orchestrating goal-directed behavior, it is not surprising that EFs are critically involved in decision-making processes. Indeed, decision-making is frequently characterized as a multifaceted process engaging various higher-order cognitive operations and appears to share substantial overlap with core components of executive functioning (Del Missier et al., 2010). Multiple lines of empirical research – including clinical observations (Balconi & Campanella, 2021) , behavioral paradigms (Snyder et al., 2015) , and neuroimaging studies (Gonzalez et al., 2005) – have provided converging evidence for the involvement of EFs in decision-making. However, despite the recurrent assumption of a close association between these domains, the precise nature of the interplay between executive control mechanisms and decision-making remains only partially understood and conceptually underdefined.

The interaction between decision-making and EFs represents a significant focus within cognitive psychology, where EFs are recognized as essential facilitators of adaptive decision-making. Core components such as inhibitory control, cognitive flexibility, and working memory play a pivotal role in shaping how individuals assess risks, weigh alternatives, and make decisions. Decision-making itself is frequently conceptualized as an integration of both cognitive and affective processes, predominantly involving activity within the PFC alongside subcortical structures – regions fundamental to the implementation of these complex EFs (Rovelli & Allegretta, 2023).

Indeed, decision-making constitutes a core cognitive and affective function through which individuals or groups discern, assess, and choose among competing alternatives to achieve specific goals or resolve problems (Swami, 2013) . This multifaceted process entails the dynamic integration of sensory information, prior experiences, personal preferences, emotional states, and situational constraints such as time pressure, social expectations, and environmental uncertainty (Balconi, 2023) . Whether enacted through rapid, intuitive judgments or slower, analytical reasoning, decision-making engages both normative frameworks – such as utility maximization – and descriptive processes, including heuristics, cognitive biases, and bounded rationality (Rovelli & Allegretta, 2023; Tversky & Kahneman, 1974) . From both evolutionary and psychological perspectives, decision-making emerges as an adaptive mechanism aimed at maximizing rewards and minimizing risks, tightly intertwined with goal-directed action and reinforcement-based learning systems (Miyapuram & Pammi, 2013) .

1.3.1 Normative frameworks of decision-making

Edwards (1954) conducted the first major review of studies on human judgment and decision making. He proposed that models based on economic and statistical theories – specifically normative and prescriptive models – should be of interest to psychologists studying how people make decisions. Edwards introduced Subjective Expected Utility (SEU) theory, which breaks down decisions into two key parts: beliefs (interpreted as probabilities) and preferences (understood as values or utilities). The theory outlines a method for combining these elements to evaluate the overall utility of a potential outcome (van der Pligt, 2015) .

The principle of maximizing utility is regarded as a suitable normative guideline for decision-making under conditions of risk or uncertainty. SEU theory is considered normative or prescriptive because it describes how choices should be made. Assuming its foundational assumptions are accepted, the most rational decision is the one that yields the highest expected utility.

The foundational principles of SEU theory are rooted in the work of Von Neumann and Morgenstern (1947). Their research demonstrated that if a person's decisions comply with specific axioms or rules, one can assign numerical utilities in such a way that choosing one option over another reflects a higher expected utility for that choice. Their method relies on the idea that each possible outcome of a given decision can be assigned a real numerical value that reflects the desirability or value of that outcome to the individual. The expected utility of an option is then calculated by multiplying the utility value of each potential outcome by the probability of that outcome occurring, and summing these products. In this way, favorable or unfavorable outcomes are weighted by their likelihood (van der Pligt, 2015).

1.3.2 Descriptive frameworks of decision-making

Descriptive theories of decision-making focus on explaining the actual choices people make, rather than prescribing how decisions should be made according to rational standards, as in the case of SEU models. This shift largely stems from psychologists moving away from the idealized frameworks traditionally proposed by mathematicians, statisticians, and economists (Johnson & Busemeyer, 2010) . Among the most influential descriptive theories is the *Prospect Theory*, introduced by Kahneman and Tversky (2013), based on psychological studies showing that people do not consistently prefer or avoid risk (Chick et al., 2017) .

Prospect Theory introduced four key concepts from cognitive psychology to offer a more human-centered understanding of decision making. First, it proposed a pre-decisional *editing phase*, during which individuals prepare the decision problem by simplifying information, mentally organizing potential outcomes, and discarding clearly inferior options. Second, it introduced the concept of *reference dependence*, emphasizing that people evaluate outcomes not in absolute terms, but relative to a reference point, such as their current wealth or perceived status quo. Third, the theory highlighted that people tend to evaluate outcomes differently depending on whether they are perceived as gains or losses relative to that reference point. Finally, Prospect Theory proposed that individuals do not rely on objective probabilities but instead subjectively weight them, typically overweighting small probabilities and underweighting large ones (Johnson & Busemeyer, 2010; Kahneman & Tversky, 2013).

1.3.3 Modern perspectives of decision-making

1.3.3.1 The role of emotions in decision-making: the Somatic Marker Hypothesis

The role of emotions in decision-making constitutes a complex and multifaceted dynamic that exerts a profound influence on cognitive operations within a range of affectively charged contexts, including financial decision-making, medical judgments, and routine evaluative processes. Emotions are not merely peripheral influences but are embedded within the cognitive architecture of decision-making, functioning as mechanisms that can facilitate, distort, or constrain judgment.

It is widely acknowledged that emotional states have the capacity to shape, direct, and, in some cases, reliably predict advantageous decision outcomes, thereby serving as critical resources in evaluative reasoning (Crivelli & Balconi, 2023) . This perspective is based on embodied cognition frameworks, which posit that emotional experiences – and more specifically, their associated physiological responses – constitute integral informational inputs that inform and regulate decision-making and related cognitive functions (Pace-Schott et al., 2019) .

Indeed, numerous studies affirm that emotional processes are deeply embedded within decision-making mechanisms. A key example is the *Somatic Marker Hypothesis* developed by Bechara & Damasio (2005) , which posits that emotions exert a crucial influence on choices by offering feedback derived from prior experiences. According to this theory, human behavior is shaped by expected emotional reactions to potential actions, formed through past experiences. This association between behavior and anticipated affective outcomes is regulated by the ventromedial prefrontal cortex (vmPFC) and encoded through physiological responses known as somatovisceral signals, forming the so-called "*body loop*". These bodily sensations are then internally re-created in the brain via the somatosensory and interoceptive cortices, particularly the insula, in a process referred to as the "*as-if loop*". Once established, somatic markers can be reactivated to forecast the emotional impact of different choices, thereby steering decisions toward options with the most positive emotional implications.

This model underscores that what is often deemed rational decision-making is, in fact, grounded in emotional assessment rather than pure logic. Ignoring these emotional evaluations can result in poorer outcomes. Expanding on this view, Immordino-Yang & Damasio (2007) emphasize the essential role of emotion in both learning and decision-making, arguing that choices made without emotional insight are frequently lacking depth and coherence.

1.3.3.2 Dual Process theory

From a cognitive-psychological standpoint, human cognitive capacity is inherently limited, especially when operating under complex, uncertain, and time-pressured conditions. In such scenarios, individuals often rely on simplified heuristics to make decisions (Kahneman, 2003). However, these mental shortcuts, while efficient, can lead to systematic errors or cognitive biases, often due to the neglect of relevant information (Evans, 2008; Kahneman, 2003) .

Within this framework, Kahneman (2003) connected the work he and Tversky carried out on heuristics and biases to two broad types of cognitive processing modes: Type 1 and Type 2 processing. Type 1 thinking, also referred to as System 1, is characterized by rapid, intuitive, automatic, heuristic-based, and emotionally influenced responses. It is often likened to intuition and is especially active when immediate decisions are required (Ehrlinger et al., 2016) . In contrast, Type 2 thinking, or System 2, is analytical, reflective, effortful, and underlies rational deliberation, but it requires sufficient cognitive resources, time, and information to function effectively. Biases are most likely to emerge when System 2 fails to intervene or override the intuitive impulses of System 1, leading to flawed judgments (Kahneman, 2011) .

What stands out from these modern perspectives is that emotions are recognized as a fundamental component of decision-making. While once viewed as sources of bias and poor judgment, emotions are now seen as essential for integrating cognition and behavior. Anticipated emotions can broaden our perspective on potential outcomes, while immediate affect helps focus attention, but may also lead to decisions that conflict with long-term interests (van der Pligt, 2015).

Having examined the main theoretical models of decision-making, it becomes essential to explore its underlying neural mechanisms. Particular attention will be given to prefrontal structures, which play a pivotal role in integrating cognitive control, affective input, and behavioral regulation.

1.4 Neural underpinnings of decision-making

Understanding the neural mechanisms underlying decision-making has long been challenging and often viewed as too complex a topic to address effectively. The process involves numerous interacting components, and a wide range of behaviors involving elements of choice, further complicating the issue. However, recent interdisciplinary research – including neuroimaging, patient studies, electrophysiological recordings, and animal experiments – has begun to shed light on some of the fundamental questions surrounding brain mechanisms of decision-making (Krawczyk, 2002).

The emerging understanding suggests that the PFC can be functionally divided into three main regions: the orbitofrontal areas (OFC), the dorsolateral prefrontal cortex (DLPFC), and the anterior cingulate cortex (ACC). Each of these regions contributes in distinct ways to the complex cognitive operations involved in decision making. Rather than operating as isolated units, these areas are thought to participate in broader neural networks, each supporting different aspects of the decision-making process (see Figure 5). This functional segmentation reflects both the specific roles of these prefrontal subregions and their unique patterns of connectivity with other parts of the brain.

Importantly, this does not imply that the PFC consists of autonomous modules acting independently, but rather that different parts of it are integrated into distinct, multi-component systems, each specialized for particular cognitive functions relevant to decision-making (Krawczyk, 2002).

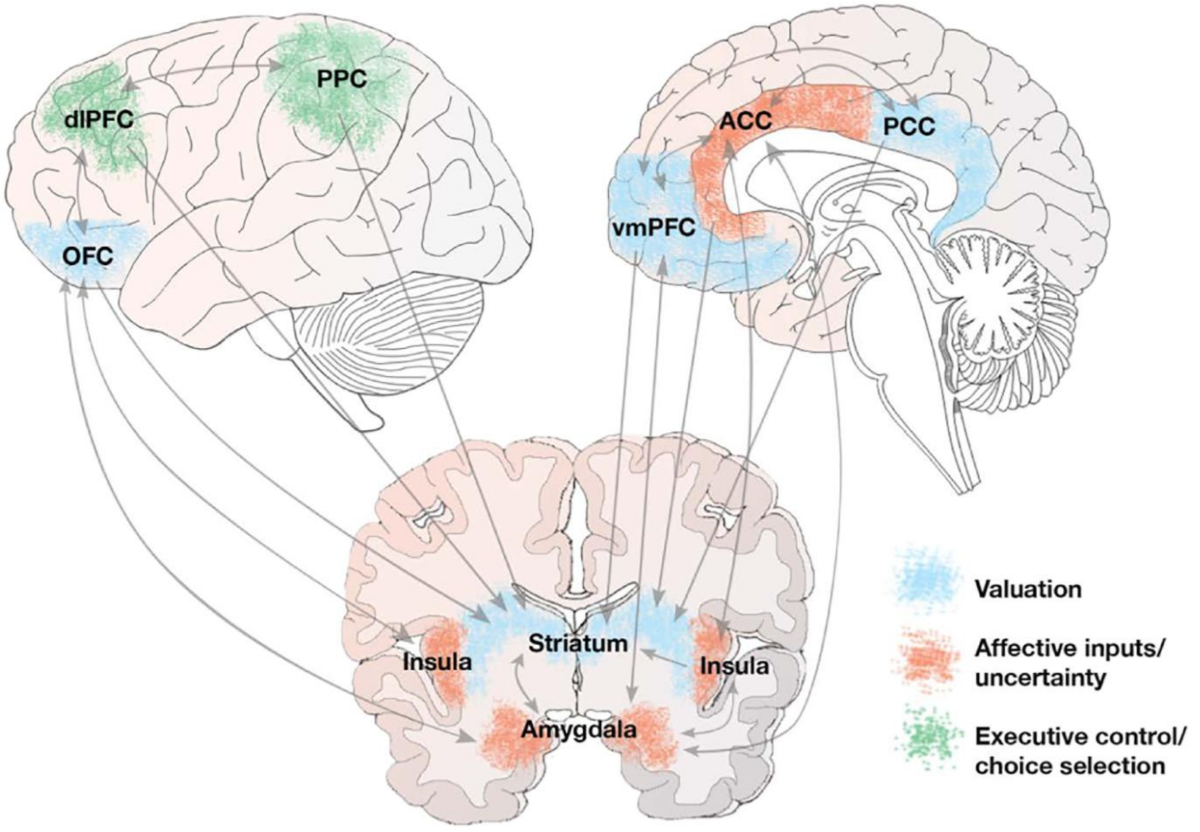

Figure 5. Graphical representation of the main brain areas involved in decision-making process (from Guttman et al., 2018).

1.4.1 The role of orbitofrontal cortex

The OFC plays a central role in decision-making, particularly in evaluating the emotional and reward-related value of stimuli (Rolls, 2023) . Acting as an integration hub for affective signals from the limbic system, the OFC helps shape the emotional tone of decision options and contributes to intuitive “gut feelings” often involved in complex choices. It is especially important in decisions driven by outcomes, both tangible, such as financial gains or losses, and abstract, such as social approval or praise (Breiter et al., 2001; Knutson et al., 2000) . The OFC supports behavioral flexibility by adapting responses to shifting reward contingencies and inhibiting actions toward no longer rewarding stimuli, which is vital under time pressure or changing circumstances (Krawczyk, 2002) .

Structurally, the OFC is highly interconnected with the amygdala, basal ganglia, and other prefrontal regions, allowing it to process perceptual and emotional information, assess it in terms of reward value, and interact with regions like the DLPFC involved in higher-order reasoning (Berns et al., 2001; Cavada et al., 2000; Hikosaka & Watanabe, 2000). This places the OFC at the intersection of emotion and cognition, where it helps align motivational states with decision outcomes. Beyond influencing initial choices, the OFC also contributes to post-decision experiences such as satisfaction or regret, particularly through its involvement with dopaminergic reward circuits. In this way, the OFC helps link knowledge, emotion, and appropriate action during decision making (Rolls, 2023) .

1.4.2 The role of dorsolateral prefrontal cortex

The DLPFC is crucial for maintaining and manipulating information in working memory, a function fundamental to decision-making. It allows individuals to track goals, evaluate competing options, and retain relevant emotional or contextual information. Beyond working memory, the DLPFC is also involved in various forms of reasoning, including hypothesis testing, inductive inference, and the categorization of novel stimuli, all processes essential for making decisions, especially in unfamiliar or ambiguous situations (Krawczyk, 2002) .

Research suggests a hemispheric specialization within the DLPFC: the right DLPFC becomes more engaged during uncertain, complex, or poorly defined decisions, where reliance on memory and flexible thinking is key (Mohr et al., 2010) . It is particularly active when decisions must be made without clear rules or when evaluating novel options. In contrast, the left DLPFC appears more involved in structured decision-making scenarios – those with clear constraints, fewer options, or predefined reward values – drawing more heavily on immediate environmental cues (Panidi et al., 2022) . Altogether, the DLPFC supports the deliberative, goal-directed components of decision-making, especially when conscious evaluation, comparison, and reasoning are required (Krawczyk, 2002) .

1.4.3 The role of anterior cingulate cortex

The ACC is particularly engaged during decision-making under high uncertainty and conflict. Neuroimaging studies suggest that the ACC becomes active when choices are ambiguous, when multiple competing responses are possible, and when there is a high risk of making errors. It is thought to play a central role in conflict monitoring, detecting discrepancies between competing options or internal goals and helping to guide attention and processing toward the most relevant information (Botvinick et al., 2004) .

Beyond its role in identifying cognitive conflict, the ACC also appears involved in decisions involving risk and reward, especially in dynamically changing contexts. It is active both before and after outcomes are revealed, indicating a function in monitoring results and signaling the need for behavioral adjustment when necessary (Shenhav et al., 2013). Rather than making decisions directly, the ACC may serve as a mediator, integrating signals of conflict, error, or outcome and coordinating responses across other brain regions, such as the OFC and DLPFC, to optimize decision strategies (Krawczyk, 2002) .

1.5 How feedback shapes decision-making: a cognitive perspective

Behavior, and consequently our decisions, are fundamentally shaped by the dynamic interaction with our environment (Cohen et al., 2007) . Environmental signals play a key role in this process, as they provide feedback that helps determine whether an action or decision was effective. This feedback is essential for adaptively refining behavior and enhancing task performance (Cunillera et al., 2012) . On one hand, such outcome-related cues support the consolidation of the current strategy by confirming (or disconfirming) its success, known as outcome-based behavioral adjustment. On the other hand, environmental stimuli can also indicate the need to shift strategies, prompting the adoption of new rules for processing future inputs, referred to as rule-based behavioral adjustment (Cunillera et al., 2012) . The capacity to flexibly interpret and respond to environmental cues is a key aspect of higher-order metacognitive executive functions, which, as previously seen, encompass abilities such as planning, problem-solving, maintaining information in working memory, and monitoring performance (Burgess et al., 2000; Cunillera et al., 2012).

While the effectiveness of cognitive control mechanisms depends on the strength of task goal activation, adaptive learning additionally requires the evaluation of both positive and negative outcomes, and similar cognitive processes may support the reinforcement of a task set. Therefore, providing clear information about the nature (positive or negative) of outcomes may be necessary to fine-tune behavior in line with task demands (Holroyd & Coles, 2002) . Research has also shown that cognitive control and reinforcement learning processes interact in subtle, implicit ways across various contexts. Indeed, to improve decision-making and understand the consequences of their actions, individuals rely on external feedback. When actions lead to negative outcomes – such as punishment or negative feedback – they are less likely to be repeated. In contrast, behaviors followed by positive outcomes – like rewards or positive feedback – tend to occur more frequently, reinforcing those actions over time (Kobza et al., 2012) .

Building on the importance of feedback in behavior regulation, cognitive processing theories offer structured explanations of how individuals mentally adapt to outcomes and adjust their behavior accordingly. Researchers have explored various mental processes – such as attention, memory, attribution, and strategy use – to explain how individuals perceive and respond to situations (Wofford & Goodwin, 1990). Klein (1989) and Lord & Kernan (1987) combined the ideas of scripts, goal setting, and control theory to explain how feedback influences behavior through cognitive processing. According to control theory, people follow an action-first approach and adjust their behavior by continuously comparing feedback with their goals. Initially, they rely on scripts, mental routines linked to familiar goals. If feedback shows that outcomes don't match expectations, they may revise or switch script tracks. If discrepancies persist or if the task is new, they move to controlled processing and explore new strategies. While scripts are efficient, they are not always accurate; indeed, they can oversimplify complex decisions and lead individuals to miss important differences between current and past situations.

According to the model proposed by Wofford & Goodwin (1990) (Figure 6) the immediate causes of decision-making are two cognitive tools: scripts and strategies. Scripts are mental structures stored in memory that help individuals recognize and act in familiar situations. When a person encounters a known scenario and receives positive or no feedback, they typically follow an existing script, this is referred to as Path 1. However, if initial negative feedback signals that performance does not meet expectations, individuals may consult a different track within the same script, an alternative sequence of actions suited to similar goals (Path 2). This can lead to a change in decision behavior, though still within the framework of familiar mental patterns. If the feedback continues to be negative or if the situation is entirely new or unexpected, the individual may abandon script-based thinking and shift toward strategy processing (Path 3). This involves constructing new, original approaches for problem-solving and adapting behavior to meet goals. Over time, if successful, these strategies may become integrated as new scripts.

For any of these changes to happen, feedback must first be noticed, interpreted, and mentally processed. This includes recognizing discrepancies between goals and results, evaluating the situation, forming expectations about outcomes, and attributing causes to success or failure. This processing can occur automatically or through conscious reflection. When individuals move into Path 2 or 3, their cognitive processing becomes more complex and diverse, involving a broader range of evaluations, predictions, and explanations. This adaptive flexibility is essential in responding effectively to changing or challenging situations (Wofford & Goodwin, 1990) .

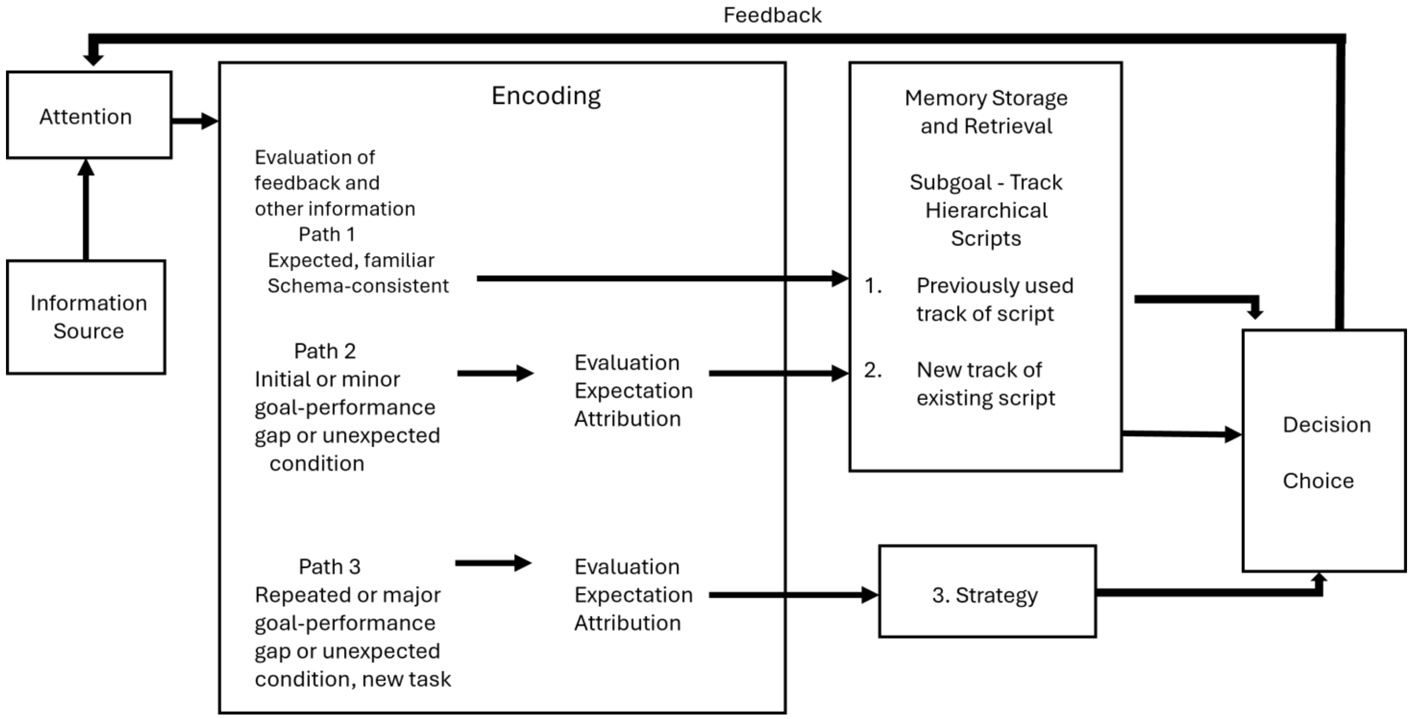

Figure 6. Cognitive-processes model for feedback and decision choice (from Wofford & Goodwon, 1990).

Interestingly, as pointed out by Mangiapanello & Hemmes (2015) several researchers have noted that feedback procedures are often applied in a way that closely resembles reinforcement or punishment strategies (P. K. Duncan & Bruwelheide, 1985; Peterson, 1982). In both feedback and operant conditioning frameworks, the consequences of a behavior depend on specific features of that behavior. This similarity likely explains why feedback is frequently considered to act as either a reinforcer or a punisher (Miltenberger, 1997; Weatherly & Malott, 2008) even though the underlying behavior regulation mechanisms are seldom examined independently.

Unlike feedback stimuli, reinforcers and punishers are categorized based on their observable effects on the behavior they follow, such as changes in likelihood, frequency, intensity, or latency. Reinforcement is defined by an increase in behavioral strength (e.g., higher rate, greater probability or intensity, or shorter latency), while the opposite pattern suggests a punishing effect. Although both feedback and operant procedures use the labels “positive” and “negative,” the meanings of these terms differ between the two contexts. In reinforcement and punishment, “positive” and “negative” refer to whether a stimulus is added or removed following a behavior. In contrast, within feedback systems, these terms typically describe the tone or content of the message – affirmative (positive) or corrective (negative) – rather than the contingency itself. Feedback is most commonly structured in a way that parallels positive reinforcement or positive punishment, meaning that feedback stimuli are generally delivered (rather than withdrawn) in response to behavior.

In their review Mangiapanello & Hemmes (2015) concludes that feedback and operant procedures frequently share parameter structures. Even when differences exist, such as delayed feedback versus immediate reinforcement or punishment, convergence is possible (Peterson, 1982) suggesting that both procedures are governed by common behavioral processes (Miltenberger, 1997; Weatherly & Malott, 2008). The authors argue that this convergence supports the "*conceptually systematic assertion that feedback phenomena are reducible to operant conditioning*," despite acknowledging the inductive nature of the argument and its vulnerability to alternate interpretations.

Ultimately, these models underscore that the efficacy of feedback depends not only on its content or timing, but on the individual's capacity for self-monitoring and metacognitive reflection. The transition from merely reacting to feedback to strategically integrating it represents a shift from reactive cognition to proactive self-regulation, an essential distinction in understanding adaptive decision-making.

1.5.1 Influences on feedback effectiveness

The effectiveness of feedback is highly variable – it can be either beneficial or detrimental – depending significantly on its characteristics and the context in which it is delivered (Hattie & Timperley, 2007; Kluger & DeNisi, 1996). A crucial factor is the type of feedback: not all feedback is equally effective, and some forms, such as praise at the "self-level," can even undermine learning. This type of feedback often reduces achievement by shifting focus away from the task and discouraging risk-taking. In contrast, corrective feedback that provides specific information on errors and offers guidance for improvement tends to be far more effective, as it promotes deeper cognitive engagement.

To explain the mechanisms behind effective feedback, Hattie & Timperley (2007) proposed a model based on three guiding questions: "*Where am I going*?", "*How am I going?*", and "*Where to next?*". Specifically, feedback can operate at four levels: the *task level* focuses on the accuracy or quality of task performance, while helpful, it is most effective when it triggers further learning; the *process level* addresses the strategies or processes used and is particularly powerful in fostering understanding and transferable skills; the *self-regulation level* supports learners' capacity to monitor and guide their own learning, enhancing metacognitive skills and resilience. In contrast, the *self-level*, often expressed as personal praise, tends to be the least effective, as it can create dependency and distract from learning goals.

Timing also plays a critical role: immediate feedback generally has stronger effects, though delayed feedback can be more beneficial for complex tasks by encouraging reflection. Equally important are the content and specificity of feedback: the most effective feedback clearly communicates what needs to be done next, rather than merely pointing out errors. This kind of feedback supports "disconfirmation" – the recognition of mismatches between expectations and outcomes – which in turn drives reflection and improvement (Butler & Winne, 1995) . Lastly, feedback is most effective when aligned with specific, challenging goals and when it builds on previous attempts; it is less effective for tasks that are overly simplistic or excessively complex (Hattie & Timperley, 2007; Kluger & DeNisi, 1996; Locke & Latham, 1990) .

1.5.2 Neural correlates of feedback processing

As pointed out in paragraph 1.5, feedback procedures are often applied in a way that closely resembles reinforcement or punishment strategies (Mangiapanello & Hemmes, 2015). This resemblance is not merely behavioral, but several research has demonstrated that performance feedback acting as an external reward activates related brain regions (Aron et al., 2004; Tsukamoto et al., 2006).

The brain's reward system is understood to be a complex, interconnected network involving areas such as the striatum, amygdala, OFC, medial prefrontal cortex, and the dopaminergic midbrain.

Notably, multiple studies have shown that positive feedback elicits greater activation in the striatal regions compared to negative feedback, with no brain areas showing a stronger response to negative feedback than to positive (Marco-Pallarés et al., 2007; Nieuwenhuis et al., 2005).

Specifically, Marco-Pallarés et al. (2007) showed that positive feedback, compared to negative feedback, elicited stronger activation in key reward-related brain regions, including the ventral striatum (nucleus accumbens), putamen, midbrain, and the anterior and posterior cingulate cortex. On the contrary, no brain regions showed greater activation during negative feedback than positive feedback. Furthermore, the midbrain and ACC exhibited a bidirectional response, with increased activation to positive feedback and decreased activation to negative feedback, suggesting alignment with known patterns of dopaminergic activity (bursts for rewards, dips for negative outcomes).

Another study (Woo et al., 2015) – investigating through fMRI how informative versus confirmatory feedback affects brain activity during negative feedback processing – found that confirmatory feedback (which simply indicates failure) activated regions linked to negative emotional responses, including the amygdala, dorsal ACC, and thalamus. In contrast, informative feedback (which explains why the response was incorrect) triggered greater activation in the DLPFC, a region associated with cognitive control and emotion regulation. Importantly, functional connectivity analysis revealed a negative coupling between the DLPFC and the amygdala during informative feedback, suggesting that task-relevant information may help regulate negative emotions implicitly.

Moreover, several studies have also focused on the electrophysiology of feedback processing in decision-making, pointing out the existence of two components of the event-related potentials (ERPs): the feedback-related negativity (FRN) and the feedback P3 (see Figure 7). The FRN is a negative deflection recorded at fronto-central sites around 250–300 ms after feedback appears and is generally stronger following negative feedback (Martín, 2012; Walsh & Anderson, 2012). According to reinforcement learning theory (Holroyd & Coles, 2002) , the FRN reflects a negative reward prediction error; thus, it signals that the outcome is worse than expected, based on prior stimulus-response associations. Some updated interpretations (Holroyd et al., 2008) attribute the observed difference between positive and negative feedback not to increased negativity, but to a reward-related positivity after positive feedback. Nonetheless, the idea that FRN activity reflects reward prediction errors remains widely accepted, and the FRN (or reward positivity) is still seen as an indicator of how feedback supports reinforcement learning.

The feedback P3, on the other hand, is a positive ERP component observed at posterior electrodes between 300 and 600 ms after feedback. It belongs to the broader category of posterior P3 waves and is associated with endogenous, attention-related processing, such as updating working memory (Polich, 2007). The P3 is thought to reflect the motivational significance of feedback (Ferdinand et al., 2012) , aligning with studies showing its sensitivity to reward magnitude and overall feedback value (Martín, 2012) .

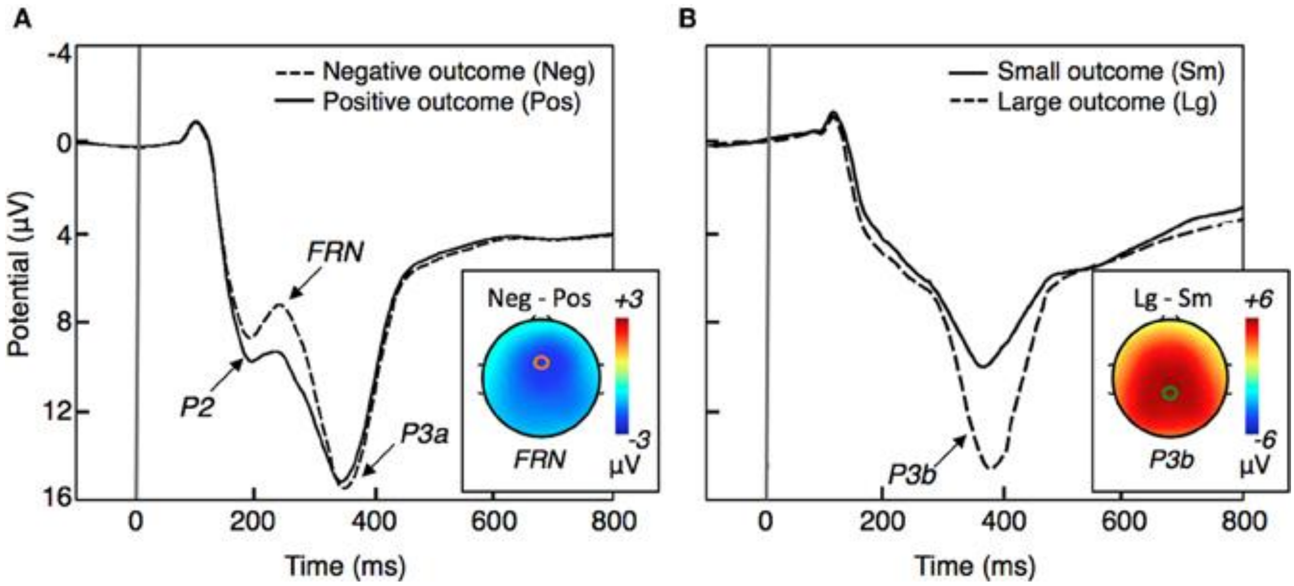

Figure 7. This figure provides a simplified illustration of typical ERP waveforms in response to different outcomes. The x-axis indicates the time elapsed since the presentation of behavioral feedback (starting at 0 ms). (A) shows ERP responses to positive and negative outcomes recorded at a fronto-central electrode, with the scalp map highlighting differences between the two around the peak of the FRN (approximately 250 ms post-feedback). (B) displays ERP responses to outcomes of high versus low magnitude at a centro-parietal site, with the scalp topography illustrating the contrast around the peak of the P3b component (typically between 300 and 600 ms after feedback) (from San Martín, 2012).

In addition to the feedback-related components, another fundamental electrophysiological marker highly relevant to metacognition and performance monitoring is Error-related Negativity (ERN). The ERN is a sharp negative deflection occurring approximately 50–100 ms after the commission of an error, maximal at fronto-central scalp sites. Unlike the FRN, which is elicited by external feedback, the ERN reflects internal error monitoring and is generated even in the absence of external cues (Olvet & Hajcak, 2008; Hajcak, 2012).

Neurophysiological and source localization studies consistently implicate the anterior cingulate cortex (ACC) as the primary generator of the ERN, supporting the idea that it reflects rapid, automatic detection of performance failures (Olvet & Hajcak, 2008). Importantly, the amplitude of the ERN has been linked to individual differences in error awareness, cognitive control, and self-monitoring, making it a central index in the study of metacognitive processes (Hajcak, 2012).

While the ERN typically captures early, automatic error detection, it is often followed by a later component, the Error Positivity (Pe), appearing approximately 200–400 ms after the response. The Pe is commonly interpreted as an index of conscious error awareness and the allocation of attentional resources to the processing of mistakes. Seminal work has shown that the Pe is dissociable from the ERN and is selectively associated with explicit awareness of errors and higher-level evaluative processes (Overbeek et al., 2005; Ullsperger et al., 2014). Together, ERN and Pe provide a complementary picture of how individuals detect, interpret, and consciously evaluate their own performance. In decision-making contexts, differentiating between internal error monitoring (ERN/Pe) and feedback-based processing (FRN/P3) is crucial for understanding how individuals integrate external information with metacognitive evaluations and adjust their behavior accordingly.

In decision-making contexts, differentiating between internal error monitoring (indexed by ERN/Pe) and feedback-based processing (indexed by FRN/P3) is crucial for understanding how individuals integrate external information with endogenous metacognitive evaluations and adjust their behavior accordingly (Hewig et al., 2007).

1.6 Centrality of metacognition in feedback processing and decision-making

As previously pointed out, for a long time, feedback has been considered a crucial factor in guiding and modifying behavior. A wide range of studies have confirmed that receiving feedback can improve how individuals perform across different tasks, such as perceptual evaluations, memory tasks, and learning exercises (Goldhacker et al., 2014; Luo & Liu, 2023). However, not all scholars agree on its universally positive impact. Some have argued that feedback can sometimes produce negative outcomes. For instance, Raftery & Bizer (2009) observed that negative feedback might trigger discomfort and reduce performance in later tasks. Similarly, feedback that is poorly matched to the person's needs can interfere with the learning process (Schreiner et al., 2015). Overall, while feedback has the potential to strongly influence behavior, its effectiveness depends on how and when it is delivered.

In recent decades, findings from both behavioral and neuroimaging research have shown that feedback is not solely managed by cognitive mechanisms but also activates metacognitive and motivational systems. This highlights the intricate interaction between emotional and cognitive processes involved in feedback processing (Lipnevich & Panadero, 2021). A variety of theoretical frameworks have been developed to explain how feedback functions, and while each emphasizes different elements, they all underscore the central role of metacognition. In essence, although these models approach feedback from various angles, they consistently recognize metacognitive processes as essential to its effectiveness. As such, adopting a metacognitive perspective is key to understanding how feedback influences behavioral outcomes (Luo & Liu, 2023).

This connection becomes especially evident in the context of decision-making, which involves the continuous accumulation of evidence from either external sensory input or internal cognitive representations (Qiu et al., 2018) . Fluctuations in this evidence can introduce uncertainty, prompting individuals to reassess or modify their choices, even in the absence of explicit feedback. Within the broader framework of cognitive control, the ability to monitor decision uncertainty and adapt behavior accordingly is a hallmark of metacognition, or "thinking about thinking" (Flavell, 1979; Fleming & Dolan, 2012) .

But what is metacognition? Metacognition can be defined as a higher-order cognitive skills that help people monitor and control their information processing (Basu & Dixit, 2022). It can take place before a cognitive task begins, when a person anticipates whether they possess the necessary knowledge and skills to tackle the task successfully. It can also occur during the task itself, as the person monitors their ongoing performance and reflects on whether their current strategies or approaches need adjustment for better outcomes. Finally, metacognition can happen after the task is completed, when the person reflects on the experience, assesses its effectiveness, and draws conclusions to inform how similar tasks should be approached in the future (Winne & Azevedo, 2014) .

Metacognition is commonly understood to consist of two main components: knowledge of one's own cognitive processes and the ability to regulate those processes (Flavell, 1979) . Knowledge about cognition involves an individual's awareness of their own cognitive processes, general understanding of cognition, the strategies they employ, and the contexts in which those strategies are most effective. This type of knowledge is typically categorized into three types: declarative, procedural, and conditional (Basu & Dixit, 2022) . In contrast, the regulation of cognition involves a set of specific processes that help manage and guide one's thinking. These include planning, monitoring, evaluating, using strategies to manage information, and correcting errors, each contributing to effective control over cognitive activity (Basu & Dixit, 2022) .

Moreover, in line with recent developments highlighting the dynamic and self-regulatory nature of metacognition, several studies conducted within the framework of a broader research program on decision-making and self-awareness have provided converging evidence on the central role of metacognition in feedback processing and behavioral regulation.

One study demonstrated that metacognitive monitoring significantly modulates the mental effort required during complex tasks, with individuals showing higher self-awareness displaying more adaptive neurophysiological patterns and reduced cognitive load (Balconi, Acconito, et al., 2023) . Additional findings indicated that metacognitive control is supported by neuro-autonomic regulation, particularly in ecologically valid contexts. Individuals with higher internal regulation showed enhanced resistance to distraction and greater stability in both cognitive performance and autonomic responses when processing corrective feedback (Balconi, Acconito, et al., 2024) . Further evidence from decision-making under risk conditions demonstrated that individuals with stronger metacognitive regulation were better able to evaluate uncertainty and adjust their choices accordingly, leading to more resilient and informed decisions (Crivelli, Allegretta, et al., 2024).

Together, these contributions support a multidimensional view of metacognition in which monitoring, strategic control, and intrinsic motivation interact with external feedback to optimize decision-making. Informative feedback, in particular, emerges as a key facilitator of metacognitive adaptation, enabling individuals to revise strategies, learn from errors, and respond flexibly in changing environments.

Another important aspect of metacognitive monitoring concerns the ability to modify one's strategy after detecting an error. Evidence from response-inhibition paradigms, such as the Go/NoGo task, shows that the detection of an error often leads to post-error slowing, a reliable behavioral marker of strategic adjustment and one of the earliest empirical signatures of adaptive performance regulation (Rabbitt, 1966). Specifically, after committing a false alarm (i.e., responding on NoGo trials), individuals tend to exhibit slower reaction times on subsequent Go trials, reflecting an adaptive shift toward more cautious responding to avoid repeating the mistake. Such adjustments have been widely interpreted as reflecting proactive recruitment of cognitive control and performance monitoring mechanisms (Danielmeier & Ullsperger, 2011). Neuroimaging works has demonstrated that this strategic modulation is supported by enhanced activation in key performance-monitoring regions, including the ACC and lateral prefrontal areas, which jointly contribute to error detection and the implementation of compensatory control (Menon et al., 2001). These findings underscore the role of error awareness not only in detecting failures but also in guiding strategic behavior, a core component of metacognitive regulation.

1.6.1 Metacognition about knowledge

As mentioned earlier, knowledge is typically categorized into declarative, procedural, and conditional. *Declarative knowledge* consists of having awareness of one's own cognitive skills, abilities, or commonly used strategies. In the context of metacognition, declarative knowledge includes personal beliefs about one's own abilities (self-efficacy), views on knowledge itself (epistemological beliefs), and understanding of tasks. It also encompasses judgments about which strategies are appropriate to use in specific situations, as well as expectations regarding their potential effectiveness (outcome expectations) (Winne & Azevedo, 2014). A key feature of this type of knowledge is that it can be expressed verbally. However, being aware of effective strategies does not necessarily mean a person will apply them. Factors such as lack of motivation, limited ability, or external obstacles may prevent their use. As a result, metacognitive declarative knowledge often has a weak relationship with actual outcomes (Veenman, 2007).

Procedural knowledge (often called *know-how*) refers to knowing how to perform the cognitive processes needed to complete tasks. These procedures may be specific to a particular domain or more general, applying across multiple areas. They can take the form of algorithms, which typically produce a desired outcome within certain statistical boundaries, or heuristics, which increase the likelihood of success but do not guarantee it (Winne & Azevedo, 2014). Procedural knowledge, gained through practice and experience, can become automatic when applied to familiar problem-solving contexts (Slusarz & Sun, 2001). Notably, initially, individuals are highly metacognitively aware because the procedure required to complete a task is difficult and demands effortful control. Over time, as parts of the procedure are learned and practiced, they become automatic, internalized as behavior sequences that no longer require conscious attention. As a result, metacognitive awareness decreases significantly, unlike declarative knowledge, of which individuals are typically always aware (Winne & Azevedo, 2014).

Finally, *conditional knowledge* involves understanding the situations in which a statement is true or a particular strategy is effective for achieving a goal. It is often expressed in an *if-then* format. This type of knowledge is crucial for adjusting and applying strategies in new or complex situations (Desoete, 2008). However, successful adaptation and transfer can be hindered by limited domain knowledge, poor monitoring, ineffective strategies, or a lack of awareness of task requirements and goals (Pintrich, 2000) .

Finally, metacognition can also be described based on the type of thinking it involves. Three key distinctions can be identified: (i) *metacognitive monitoring* involves becoming aware of how well a specific instance of metacognitive knowledge aligns with the criteria or standards set for that knowledge; (ii) *metacognitive control* uses the outcomes of monitoring to form an intention aimed at guiding thoughts and actions toward achieving a specific objective; (iii) *self-regulated learning* encompasses multiple occurrences of both monitoring and control processes, allowing individuals to adjust and manage their thinking over the course of working on a long and complex task (Winne & Azevedo, 2014) .

1.6.2 Neural correlates of metacognition

Building on the theoretical foundations of metacognition, scholars aimed to uncover its neural basis. For instance, Qiu et al. (2018) propose a comprehensive model in which metacognition – understood as the process of considering the outcome of a decision and whether it should be adjusted – is implemented by a neural system that is functionally and anatomically distinct from the system responsible for decision-making itself. Based on a novel "*decision–redecision*" paradigm, where participants were asked to make an initial decision and then immediately reevaluate it without external feedback, the study used fMRI to identify specific brain regions associated with different metacognitive processes. The results showed that the dorsal anterior cingulate cortex (dACC) was consistently activated in response to decision uncertainty and correlated with individuals' ability to monitor their own uncertainty. In contrast, the lateral frontopolar cortex (lFPC) was activated during decision adjustments and linked to metacognitive control, specifically, how effectively individuals revised their choices. The authors highlight that these two components of metacognition – monitoring and control – are behaviorally dissociable, stable across tasks, and localized in separate neural regions. Additionally, the metacognition network could be divided into subsystems, including the dACC and anterior insula for uncertainty monitoring, the lFPC for strategic control, and other areas such as the DLPFC and inferior parietal lobule whose functions may relate to general cognitive control (Figure 8).

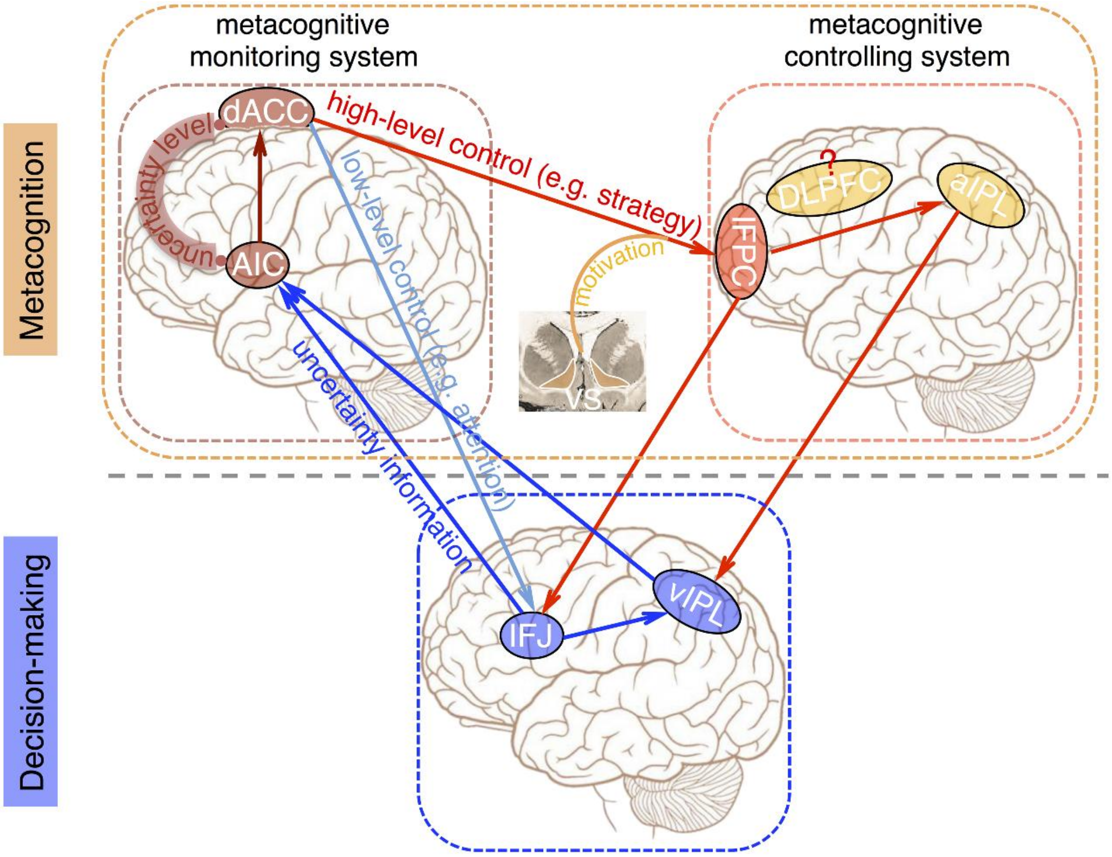

Figure 8. Functional architecture of the metacognitive neural system. This diagram illustrates the functional architecture of the metacognitive neural system and how it interacts with the decision-making neural system. The metacognitive system is made up of two main components: the metacognitive monitoring system (including the dACC and AIC) and the metacognitive control system (lFPC). Together, the decision-making system and the metacognitive system create a closed-loop network. Brain region abbreviations: AIC (anterior insular cortex), aILP (anterior inferior parietal lobule), dACC (dorsal anterior cingulate cortex), DLPFC (dorsolateral prefrontal cortex), IFJ (inferior frontal junction), lFPC (lateral frontopolar cortex), and vIPL (ventral inferior parietal lobule) (from da Qui et al., 2018).

Importantly, these systems interact within a closed-loop circuit that continuously regulates behavior in relation to internal goals. The decision-making system, primarily involving the inferior frontal junction (IFJ), is responsible for evidence accumulation and object-level cognitive operations. The metacognitive system, located in anterior PFC regions, reads out uncertainty signals from this decision process and encodes them in areas such as the dACC and anterior insula. When uncertainty is detected, the lFPC is recruited to explore alternative strategies and adjust decisions, particularly in rule-based or abstract tasks. Its engagement is further modulated by intrinsic motivation signals from the ventral striatum. Thus, the metacognitive system does not merely reflect decision confidence but actively shapes ongoing behavior through a dynamic feedback loop, monitoring internal uncertainty and triggering adaptive control mechanisms when needed.

1.7 The contribution of cognitive neuroscience to the study of decision-making

In the previous paragraphs, we have mentioned and outlined several cognitive functions and processes, including EFs, decision-making, feedback and metacognition. However, traditional tools used in cognitive psychology focus solely on the explicit aspects of the process and are vulnerable to human biases like the social desirability effect; therefore, a need for an objective approach that also accounts for and transcends individual differences emerged.

To this purpose, an unprecedented and pivotal contribution is given by neuroscience and specifically by cognitive neuroscience. Cognitive neuroscience is the scientific study of the biological foundations of mental processes such as perception, consciousness, action, memory, decision-making, language, and selective attention. Its main objective is to measure and understand brain activity underlying these cognitive functions (McClelland, 2001; Xi et al., 2011).

This discipline emerged in the 1990s at the intersection of neural sciences, cognitive psychology, and computational science. On one side, it builds on the traditions of cognitive psychology and neuropsychology, which use behavioral experiments to investigate the processes behind human cognition. It also draws from computational approaches that develop formal, mechanistic models of these mental functions. On the other side, it is grounded in behavioral, functional, and systems neuroscience, which applies neurophysiological and neuroanatomical techniques to explore how complex brain functions arise. Additionally, it incorporates findings from cellular and molecular neuroscience, providing a multi-level understanding of the brain (McClelland, 2001).

Cognitive neuroscience brings these perspectives together through the use of advanced functional brain imaging techniques, including fMRI, PET, as well as electroencephalography (EEG) and magnetoencephalography (MEG). It also benefits from the rapidly growing field of computational neuroscience, which models brain function using mathematical and algorithmic frameworks.

Nonetheless, to achieve a comprehensive understanding of complex psychological constructs, cognitive neuroscience increasingly relies on a multilevel, multimethod approach that combines neurophysiological, behavioral, and self-report data (Balconi, Acconito, et al., 2023; Balconi, Allegretta, et al., 2023; Balconi, Acconito, et al., 2024; Balconi, Rovelli, et al., 2024; Crivelli, Allegretta, et al., 2024; Morales et al., 2018; Murphy et al., 2018). This integrated methodology allows for deeper psychological inferences by linking brain activity, performance metrics, and subjective reports within a single framework.

Such an approach is particularly valuable because relying exclusively on neural data may lead to reductionist biases that overlook the complexity of behavior (Krakauer et al., 2017) . Indeed, understanding brain function requires more than just demonstrating causal links between neural circuits and behavior: behavioral analysis must precede neural investigation, as it helps define the computational and algorithmic processes involved. Without clear behavioral models and tasks, neuroscientific data risk being misinterpreted or disconnected from real-world cognitive functions (Krakauer et al., 2017; Marom et al., 2009) .

In this light, cognitive neuroscience must adopt a pluralistic model of explanation – one that balances technological advances (e.g., fMRI, EEG) with rigorous behavioral theory and experimental design. Behavioral observations are not mere adjuncts but foundational elements for interpreting neural mechanisms, especially in ecologically valid, socially embedded contexts. This integrated framework aligns with the growing recognition that neural circuits do not feel, decide, or understand, but organisms do. Therefore, studying behavior not only complements neural analysis but guides it, ensuring that neuroscience remains rooted in the phenomena it seeks to explain (Krakauer et al., 2017).

1.7.1 Electroencephalography: a methodological overview

In particular, among other neuroscientific tools, EEG allows the recording of brain electrophysiological activity in real-time and with a high temporal resolution. EEG is by far the most common non-invasive method used to measure the brain's electrical activity (Müller-Putz, 2020) . It involves placing electrodes on the scalp to detect voltage changes caused by the movement of electrical currents in and around neurons. With a history spanning nearly 100 years, EEG has developed a broad range of applications. Initially focused on clinical diagnosis, it has more recently expanded into areas such as neurorehabilitation guided by brain activity. Beyond clinical use, EEG has been a valuable tool in experimental psychology for identifying brain activity linked to cognitive processes. It has also gained recognition as a legitimate neuroimaging technique, especially with recent developments in translational and computational neuroscience. Thanks to its adaptability and ease of use, combined with modern advancements in signal processing, EEG continues to offer innovative possibilities, proving that even a well-established technology can evolve and stay relevant (Biasiucci et al., 2019).

It's important to note that EEG captures only a limited portion of the brain's electrical activity. Nonetheless, while it must deal with physiological artefacts (e.g., from heart, eyes, muscles) and environmental noise (e.g., power lines, screens), EEG can still isolate brain-specific signals.

Importantly, EEG does not detect action potentials (brief spikes traveling along axons) but instead measures postsynaptic potentials, slower voltage changes triggered by neurotransmitter activity (Biasiucci et al., 2019; Müller-Putz, 2020). The EEG signal arises primarily from the synchronous activity of pyramidal neurons in the cortex, whose aligned, columnar structure enables the formation of current dipoles, with opposing intracellular and extracellular flows between dendrites and soma. These dipoles are the main sources of EEG (Biasiucci et al., 2019).

To be measurable at the scalp, neuronal activity must be both spatially and temporally synchronized, allowing electrical fields to summate and propagate through brain tissue and surrounding layers (e.g., cerebrospinal fluid, skull, skin). Due to attenuation and spatial smoothing, EEG reflects mostly low-frequency, surface cortical activity, while deeper or misaligned sources contribute less

Several research indicate that varying degrees of brain integration – facilitated by spatial and temporal synchronization across multiple frequency bands – may be crucial for the development of perceptions, memories, emotions, thoughts, and behaviors (Knyazev, 2012). This suggests that distinct cognitive and emotional functions are likely linked to specific brainwave frequencies. Specifically, brain oscillations, whether ongoing or triggered by specific events, are typically classified into five frequency bands: delta (0.5–3.5 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (above 30 Hz) (Knyazev, 2012) (see Figure 9). These bands can be meaningfully grouped into two main categories. Delta, theta, and alpha waves represent what are known as global processing modes. These slower oscillations typically cover broad areas of the cortex and are believed to support the integration of activity across distant brain regions by promoting synchronized neural firing and phase coupling. In contrast, beta and gamma waves (referred to as local EEG modes) are faster, lower in amplitude, and confined to more localized cortical regions (Nunez & Williamson, 1996).

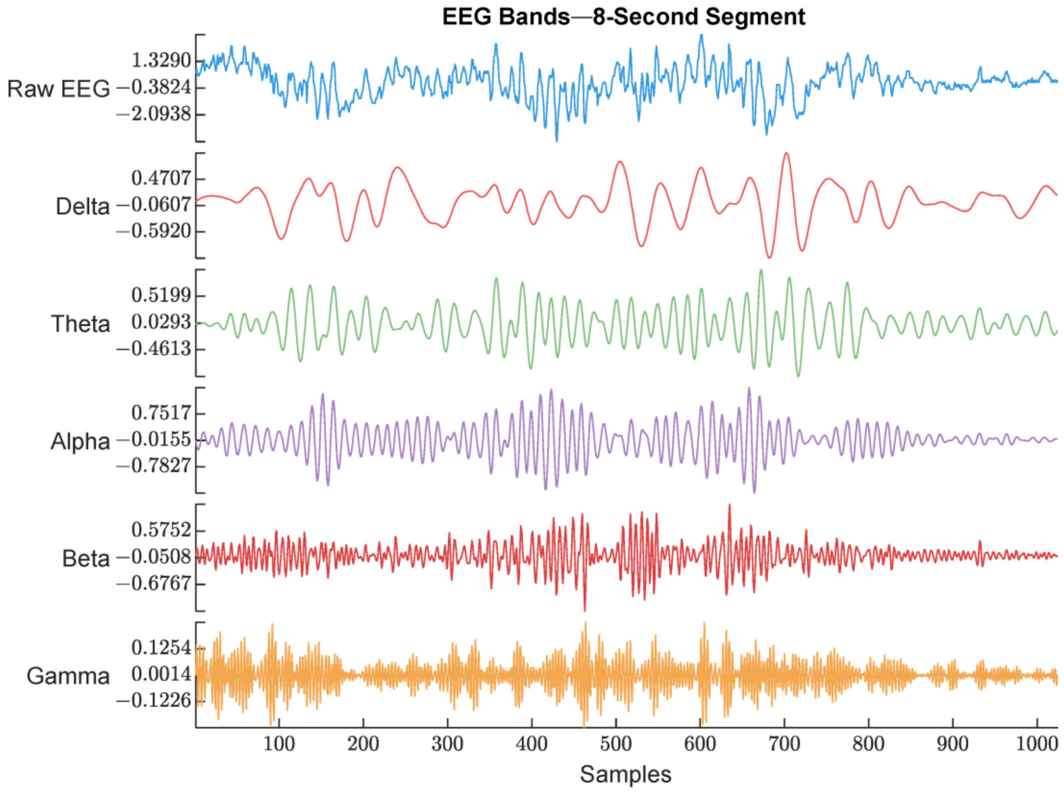

Figure 9. The raw EEG signal along with its derived frequency bands. The illustration displays examples of each EEG band shown in a different color. From top to bottom, the waveforms are labeled according to their respective bands: raw EEG, delta, theta, alpha, beta, and gamma (from Deen et al., 2025).

Over time, nearly all cognitive functions have been linked to event-related EEG oscillations. However, it is important to underline that since there are far more cognitive processes than the five primary frequency bands (delta, theta, alpha, beta, gamma), a one-to-one correspondence is unlikely. Instead, EEG oscillations likely support multiple cognitive functions, depending on their location in the brain and characteristics such as amplitude, frequency, phase, and coherence (Herrmann et al., 2016). This idea is supported by several key assumptions: (i) different brain areas have distinct functions, based on their unique neural structures (Brodmann, 1909) ; (ii) low-frequency EEG rhythms may reflect large-scale network activity, while high-frequency rhythms often indicate localized neuronal processes, contributing to the typical 1/f EEG spectrum (Singer, 1993) ; (iii) synchronized oscillations between distant brain regions may signal functional interaction (Siegel et al., 2012) ; (iv) building on this, high-frequency coherence may link nearby regions, whereas low-frequency coherence may support long-range communication (Stein & Sarnthein, 2000).

However, we provide a brief summary of the link between event-related EEG oscillations and cognitive functions, emphasizing well-established and consistently replicated findings.

Delta. Delta waves have traditionally been linked to cortical inhibition, yet growing evidence suggests they also reflect active cognitive processes, including the formation of explicit and declarative memories and emotional states (Balconi, Rovelli, et al., 2024; Hobson & Pace-Schott, 2002; Knyazev, 2012) . Delta power increases have been observed during tasks that demand focused attention and cognitive effort. These oscillations typically originate from the frontal and cingulate cortices and, due to their low frequency, engage widespread neural networks. This broad engagement may serve an inhibitory function, selectively suppressing irrelevant information to enhance focus, supporting their proposed role in attentional control (Harmony, 2013; Herrmann et al., 2016).

Theta. Theta oscillations, typically prominent over mid-frontal regions, are closely linked to attention, memory, emotional processing, and social decision-making (Khader et al., 2010; Sauseng et al., 2010). The ACC is frequently identified as a key source of these rhythms (Pizzagalli, 2007). Additionally, frontal theta oscillations are observed during executive control tasks, where they are thought to support functional inhibition, helping to regulate activity in other brain areas (Huster et al., 2013).

Alpha. Alpha oscillations are mainly associated with the inhibition of irrelevant or distracting cognitive processes (Knyazev, 2007). Typically generated in posterior brain regions, increased alpha activity in specific areas suggests those regions are not essential for the current task and are functionally suppressed (Klimesch et al., 2007; Sadato et al., 1998). Alpha rhythms are modulated by sensory input (Schürmann & Başar, 2001) and are involved in memory (Klimesch, 1997) and attention (Hanslmayr et al., 2011). Alpha waves may serve dual roles in inhibition and timing, acting as core mechanisms for cognitive processes requiring both selection and suppression.

Beta. Beta oscillations increase during states of attention and alertness, likely reflecting heightened excitatory activity associated with arousal, focused attention, and cognitive engagement (Engel & Fries, 2010; Pizzagalli, 2007; Wróbel, 2000). In visual working memory tasks, beta activity is often observed in posterior brain regions (Gola et al., 2013). Moreover, while beta rhythms are strongly linked to motor activity (Neuper & Pfurtscheller, 2001) they also vary during cognitive tasks that involve sensorimotor integration (Kilavik et al., 2013). Notably, a theory proposes that beta activity appears whether the current sensorimotor state is expected to remain stable or is about to change (Engel & Fries, 2010) .

Gamma. Unlike low-frequency oscillations, which are often linked to functional inhibition, high-frequency gamma oscillations are generally considered markers of cortical activation (Merker, 2013) . Depending on the specific brain region, gamma activity is closely associated with attentional processing, the active maintenance of memory content and conscious perception (Herrmann et al., 2016) .

1.8 Aims of the current project

As seen in the previous paragraphs of the introduction, in the field of cognitive neuroscience, decision-making has emerged as one of the most complex and ecologically relevant expressions of executive functioning, requiring the integration of cognitive control, emotional regulation, and metacognitive monitoring (Miller & Cohen, 2001) . Far from being a purely rational process, decision-making is increasingly conceptualized as a dynamic interplay between “cold” cognitive components (such as working memory and inhibition) and “hot” affective and motivational systems, often modulated by feedback and context (Diamond, 2013; Zelazo & Carlson, 2012) .

Despite this complexity, empirical studies have often analyzed these components in isolation, limiting our understanding of how they function in real-life situations. In particular, how feedback valence (i.e., whether the outcome of a decision is framed positively or negatively) influences the recall and evaluation of past decisions is still unclear, especially when considering the neurophysiological correlates of such processes in healthy populations. Moreover, while the role of metacognition in decision-making is widely acknowledged (Flavell, 1979; Fleming, 2023), few studies have investigated the "second-order" metacognitive level, that is, the individual's ability to reflect upon and regulate their own strategic planning during complex decisional tasks.

Therefore, building on the theoretical and neuroscientific foundations outlined in the previous sections, this doctoral project aims to investigate the dynamic interplay between EFs, decision-making processes, metacognition, and feedback, within an integrated cognitive-neuroscientific framework. Acknowledging the complexity and multidimensional nature of these constructs, which often lack a universally accepted definition, the project embraces a multi-level neuroscientific approach. This integrated methodology overcomes the limitations of purely behavioral analyses by offering a more objective and in-depth perspective on the underlying mechanisms of the mentioned processes, through the combination of behavioral and electrophysiological data, particularly via EEG.

Additionally, among the main goals of the project is the investigation of these cognitive phenomena through ecologically valid paradigms and, importantly, through the adoption of wearable technologies. In line with the necessity of studying cognition "*in the wild*" (Bleichner & Debener, 2017) the project aims to bridge the gap between controlled laboratory tasks and real-world decision-making contexts. The use of wearable EEG devices, in particular, allows for the monitoring of neurocognitive states in more naturalistic environments, capturing the dynamic interplay between cognitive control, feedback processing, and metacognitive regulation as they unfold in everyday-like situations.

Therefore, starting from the abovementioned objectives, three different studies were designed, implemented and run. Specifically, the first study of this project aims to investigate how the valence of feedback (positive vs. negative) shapes the recall of previously made decisions. Using an ecologically valid decision-making paradigm with real-life scenarios and EEG measurements, the study examines behavioral accuracy, errors, and response times, along with patterns of neural activity across frequency bands (delta, theta, alpha, beta, gamma) during decision-memory retrieval. Particular attention will be given to the influence of cognitive-emotional biases on memory processes, such as the positivity bias (the tendency to recall more favorable events), the negativity bias (the prioritization of negative information due to its evolutionary relevance), and the mnemic neglect effect (the tendency to disregard self-threatening feedback). These mechanisms will be explored to provide new insights into how emotional valence and prior experience modulate memory recall, offering a more comprehensive understanding of emotionally influenced memory dynamics within decision-making contexts.

The second study primarily focuses on decision-making flexibility in response to external feedback, examining how individuals choose to maintain or revise their decisions when confronted with positive, negative, or absent feedback in realistic scenarios. Special emphasis is placed on cognitive biases such as the status quo bias – the tendency to persist with previous choices even when faced with unfavorable information. The study will identify behavioral patterns reflecting such inertia and explore their neurofunctional correlates as indicators of cognitive effort and emotional engagement during decision revision. In addition, the study investigates how individual differences, including personality traits and decision-making styles, modulate both behavioral performance and metacognitive evaluations. Using validated psychometric instruments, the project explores how dispositional factors interact with executive and metacognitive processes. The ultimate aim is to identify individual profiles that either facilitate or hinder strategic control and adaptive behavior in decision-making contexts.

Finally, the third study focuses on a more advanced form of metacognition – namely, the awareness and regulation of metacognitive control over strategic planning – distinguishing it from first-order cognitive knowledge and monitoring. This form of second-order metacognition will be investigated through a modified version of the Tower of Hanoi task, combined with EEG recordings. The study aims to examine how strategic planning is associated with metacognitive beliefs and electrophysiological markers. Behavioral performance and neural activity will be analyzed in relation to participants' willingness to revise or maintain their planning strategies. Additionally, a dedicated 5-item metacognitive scale will be used to assess key dimensions: overall use of strategic planning, awareness of strategy, changes in strategy, perceived effectiveness, and retrospective willingness to adjust one’s approach. This will allow a clearer differentiation between executive functioning and higher-order metacognitive awareness, offering insight into how current cognitive effort is linked to the intention to modify future strategies.

As this overview demonstrates, EFs, metacognition, and decision-making are deeply intertwined, forming a dynamic and interdependent system in which cognition, emotion, and feedback continuously interact. Therefore, by integrating behavioral performance, EEG measures, and individual differences, this project aims to contribute to a more nuanced understanding of decision-making as a dynamic interaction between cognitive control, emotional feedback, and metacognitive regulation.

Chapter 2 – Study 1: The impact of feedback valence on decision recall: neurophysiological evidence[1]

2.1 Introduction

To gain a clearer understanding of the outcomes of a decision and to improve future decision-making, people need feedback from external sources. Behaviors that lead to negative outcomes, such as punishment or negative feedback, are less likely to be repeated, while those that produce positive results, like rewards or positive feedback, tend to encourage the behavior to occur more often (Kobza et al., 2012) .

The fundamental role of feedback in shaping behavior is clear and well-documented by several research (Balconi, Angioletti, et al., 2024; Crivelli et al., 2023; Mangiapanello & Hemmes, 2015) , yet its influence extends beyond immediate decision-making, affecting how individuals remember and learn from their experiences. Feedback, whether positive or negative, not only guides future actions but also plays a pivotal role in how well these experiences are encoded and later recalled (Hattie & Timperley, 2007) . Notably, research indicates that the valence of feedback significantly influences memory recall: a study by Höltje & Mecklinger (2020) demonstrated that positive feedback improves memory encoding, resulting in better recall compared to negative feedback. This is consistent with findings from Albrecht et al. (2023) , who observed that immediate positive feedback can affect recall, implying a complex interaction between feedback valence and memory processes.

Studies conducted on healthy individuals suggest that they frequently exhibit a positivity bias, tending to remember events as more favorable than they were (Levine et al., 2012; Schacter et al., 2011) . This bias likely stems from an adaptive mechanism aimed at preserving self-esteem if perceived as threatened. Indeed, because self-threatening information tends to be distressing, people

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[1] This paper can be found at the following bibliographic reference: Balconi, M., Angioletti, L., & Allegretta, R. A. (2025). Which type of feedback—Positive or negative-reinforces decision recall? An EEG study. *Frontiers in Systems Neuroscience*, *18*, 1524475. https://doi.org/10.3389/fnsys.2024.1524475

make considerable efforts to eliminate such memories (M. C. Anderson & Green, 2001; Gagnepain et al., 2014) . The mnemic neglect effect (MNE) further explains (Sedikides & Green, 2004, 2006) this selective forgetting suggesting that individuals are driven to protect or enhance the positivity of their self-concept and tend to disproportionately overlook the processing of negative, self-threatening feedback. As a result, self-threatening feedback is processed superficially, resulting in weaker recall due to shallow processing.

Nonetheless, some research also showed that human cognition and behavior are influenced by a negativity bias, where people tend to prioritize negative information over positive information across different psychological contexts (Norris et al., 2019) . This bias is believed to have evolved as a survival mechanism, with avoiding harmful stimuli being more essential to survival than seeking out beneficial ones (Norris et al., 2019) .

To better understand how different feedback valence affects the recall of a decision, important support comes from neuroscience through the use of electroencephalography (EEG). Indeed, brain activity related to specific perceptual, cognitive, and emotional processes can be examined through the analysis of EEG frequency bands (delta, theta, alpha, beta, and gamma) and the interpretation of their functional significance providing deeper insights into the neural mechanisms underlying these processes. Notably, low-frequency bands (delta and theta) generally exhibit an increase during emotional processes (Balconi et al., 2015, 2019), while high-frequency bands (alpha, beta and gamma) are typically associated with cognitive effort, processing, engagement, and mechanisms of focused attention (Engel & Fries, 2010; Pizzagalli, 2007; Wróbel, 2000) .

To the best of our knowledge, there are limited researches focusing specifically on the recall of decisions influenced by varying feedback valence in healthy populations. Therefore, our study combined behavioral measures – response accuracy, errors and response times (RTs) – with electrophysiological data to investigate how decision-makers recalled previously made decisions under different feedback valences. In the first part of the task, participants were presented with 10 real-life decision-making scenarios where they could choose between two alternatives. Regardless of their choice, all participants received either immediate negative feedback for five scenarios and immediate positive feedback for the other five. In the second part of the task, participants were asked to recall their responses for each scenario.

Based on previous considerations, firstly we explored potential differences in response accuracy and errors for the recall of decisions based on feedback valence. We expected to find that participants would accurately recall decisions associated with positive feedback more than those linked to negative feedback. Research suggests that healthy individuals often exhibit a positivity bias, remembering events more favorably than they were (Levine et al., 2012; Schacter et al., 2011) , which serves to preserve self-esteem. This can be explained by the MNE (Sedikides & Green, 2004, 2006) , which suggests that individuals tend to process self-threatening feedback superficially, resulting in poorer recall of negative information. We also investigated differences in RTs in recalling decisions based on feedback valence, since they serve as indicators of information processing, cognitive effort, and decision workload (Balconi, Acconito, et al., 2024) . We expected longer RTs for accurately recalled decisions with positive feedback compared to those with negative feedback. Indeed, while positive stimuli are typically easier to remember, attentional biases toward them may slow cognitive processing and memory retrieval, resulting in slower RTs (Thoern et al., 2016).

Secondly, we expected a different pattern of activity for EEG frequency bands for both accurately and incorrectly recalled decisions with positive and negative feedback. Specifically, we anticipated a crucial role of high-frequency bands: we expected a general decrease of alpha band mainly in frontal areas in the recall of decisions despite feedback valence. Indeed, alpha oscillations act as gatekeepers in neural processes, influencing how attention is directed and how stored information is accessed during tasks (Knyazev, 2013). Particularly, higher alpha activity in certain areas of the brain may indicate that region is not essential for processing information, thus its activity is suppressed while other brain regions play a more significant role in the process (Klimesch et al., 2007). On the other hand, we expected also gamma and beta to increase during the recall of decisions since beta oscillations are thought to support top-down control processes that support retrieving information from memory (Miller et al., 2018), whereas gamma oscillations are associated with the encoding and retrieval of specific memory traces, which help improve the accuracy of recalled information (Lundqvist et al., 2016).

2.1 Method

2.1.1 Sample

A total of 20 participants were selected for this pilot study (Mean age = 37.35, Standard Deviation age = 15.05, age range: 22–61, with 8 males). Exclusion criteria encompassed a history of psychiatric or neurological disorders, significant head injuries or strokes, undergoing therapy with psychoactive drugs that could influence cognitive abilities or decision-making. All participants had normal or corrected vision and hearing. Participation was voluntary, with no financial compensation provided. Each participant gave written informed consent prior to the study.

The study received approval from the Ethics Committee of the Department of Psychology at the Catholic University of the Sacred Heart in Milan (approval code: 125/24 – "Evaluating Decision-Making: Awareness and Metacognitive Decision-Making"; approval date: 23rd July 2024) and was carried out in accordance with the Declaration of Helsinki (2013) and GDPR regulations (EU Regulation 2016/679) and its ethical standards.

2.1.2 Procedure

After receiving an explanation of the experimental procedure and providing informed consent, participants were seated comfortably approximately 80 cm from a computer, wearing a wearable EEG device and completed the experimental task – delivered through an online platform (PsyToolkit, version 3.4.4) (Stoet, 2010, 2017) – in a quiet environment.

2.1.3 Decision recall task

The experimental task was structured to examine the influence of positive and negative feedback on the recall of a previously made decision, and it was divided into two phases. In the first phase (decision-making phase), participants were shown a scenario explaining they were starting their first day at a new job and that they needed to make some decisions throughout the day (e.g., "*You have just been hired at a new company and are unfamiliar with the structure. You start your first day and need to complete some bureaucratic tasks.*"). They were then given ten scenarios and asked to choose between two options, selecting the one they believed was most appropriate. After each decision, feedback about the consequences of their choice was displayed. Regardless of the option chosen, five scenarios always provided positive feedback (e.g., "Perfect, now you know where the office is!") and five provided negative feedback (e.g., "This decision wasted a lot of time; you should have made a different choice!"). Instead, the second phase (recall phase) aimed to assess the accuracy of participants' recall regarding their initial decisions. Participants were presented with the same scenarios from the first phase and asked to indicate which option they chose (see Figure 10). Behavioral data, including participants' accuracy (ACC), errors (ERRs) and response times (RTs) for each scenario were collected.

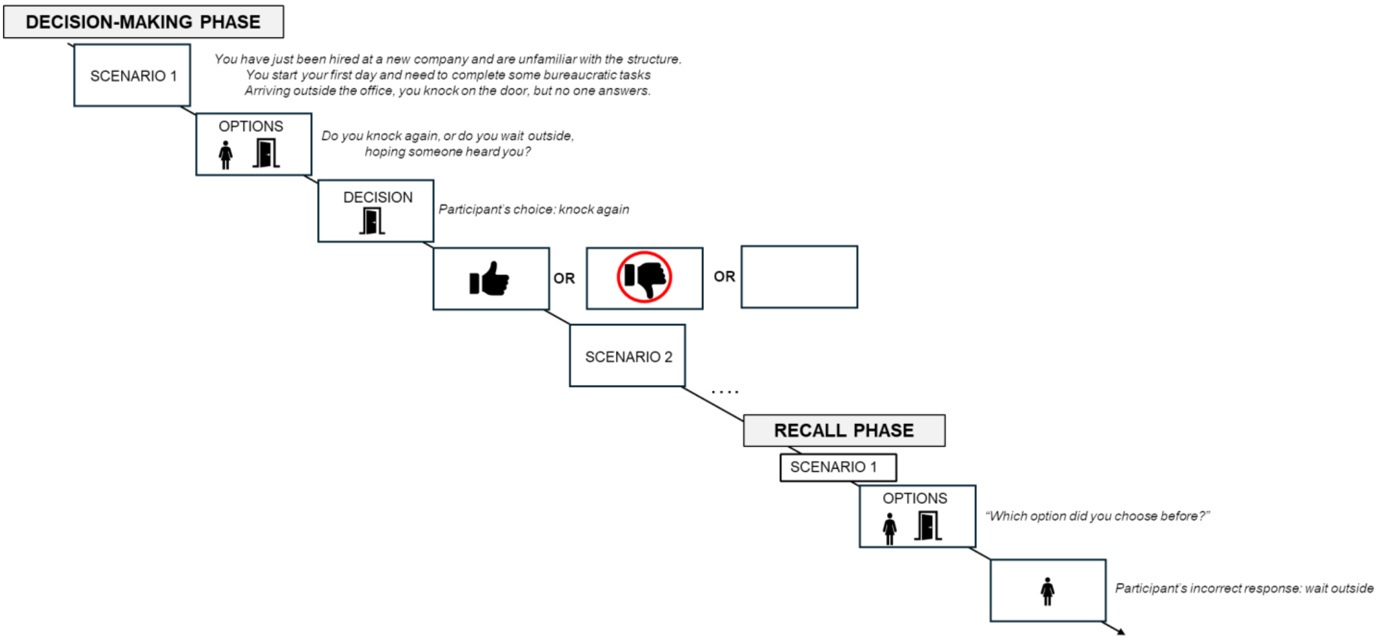

Figure 10. Figure represents the experimental procedure.

Specifically, ACC was calculated as the number of correctly recalled decisions on the total amount of decisions for both positive and negative feedback, ERRs were calculated as the number of wrongly recalled decisions on the total amount of decisions for both positive and negative feedback.

2.1.4 EEG data acquisition and processing

EEG data were collected for 120 s during both a resting state and while participants completed the recall phases of the task using a wearable, non-invasive EEG device, the Muse™ headband (version 2; InteraXon Inc., Toronto, ON, Canada). This system detects spectral activity across standard frequency bands (delta, theta, alpha, beta, and gamma) using seven dry electrodes made from conductive silver material and silicone rubber. The electrodes are arranged according to the 10–20 system (Jasper, 1958), three functions as reference points, while the remaining four are positioned on the left and right sides of the forehead: two in the frontal area (AF7 and AF8) and two in the temporoparietal area (TP9 and TP10). The data were sampled at 256 Hz, with a 50 Hz notch filter applied, and recorded via a system featuring an accelerometer, gyroscope, and pulse oximetry, all synced through the Mind Monitor mobile app via Bluetooth. Participants were instructed to minimize eye movements and blinking to reduce potential artefacts, which were later manually removed through visual inspection. These artefacts included blinks, jaw clenching, and movement. EEG data from each electrode and frequency band were converted in real time into Power Spectral Density (PSD) using Fast Fourier Transformation, applied across the delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–44 Hz) bands. Power variations during task performance were calculated by comparing the power values during the task with baseline values.

The EEG data was recorded during the recall phase as participants recalled the decisions previously made, involving a choice between two distinct options. Following data acquisition, the EEG signal underwent an offline segmentation procedure. This process involved segmenting the signal according to the feedback associated with each decision outcome in the first phase of the task (i.e., decision-making phase), categorizing segments into those associated with positive and negative feedback and further differentiating between correct and incorrect responses. This segmentation enables a comprehensive analysis of the neural activity patterns underlying distinct decision outcomes and feedback types, facilitating a deeper understanding of the cognitive mechanisms involved in decision-making.

2.1.5 Data analysis

The assumption of normality for the distribution was preliminarily tested and confirmed through the application of kurtosis and skewness tests. Based on this evidence, four distinct repeated measure ANOVAs with Feedback (2: positive, negative) as independent within variables was applied to the ACC and RTs of correctly recalled decisions (i.e., correct responses), to ERRs (i.e., incorrect responses, which are wrongly recalled decisions) and to the RTs of the incorrect responses as dependent variables.

Regarding EEG data, four distinct repeated measure ANOVAs with Feedback (2: positive, negative) and Electrode (4: AF7, AF8, TP9, TP10) as independent within variables was applied to the variations of EEG frequency bands for segments related to correct and incorrect responses of recalled decisions as dependent variables. When required, the degrees of freedom for each ANOVA test were adjusted using the Greenhouse–Geisser epsilon. Following this, significant interactions were explored through pairwise comparisons to examine simple effects. To control potential biases due to multiple comparisons, the Bonferroni correction was applied. The effect sizes for statistically significant results were quantified using eta squared (η^2), with a significance threshold set at $\alpha = 0.05$.

2.2 Results

2.2.1 Behavioral results

A main effect was found for Feedback [$F(1,19) = 7.96$, $p = 0.011$, $\eta^2 = 0.079$], for which we observed higher RTs for the correctly recalled decisions with a positive ($M = 9.09$, SE = 0.583) compared to negative feedback ($M = 7.69$, SE = 0.506) (Figure 11a).

No other significant effects were found for the ACC of recalled decision, ERRs and RTs of the errors (all $p > 0.05$).

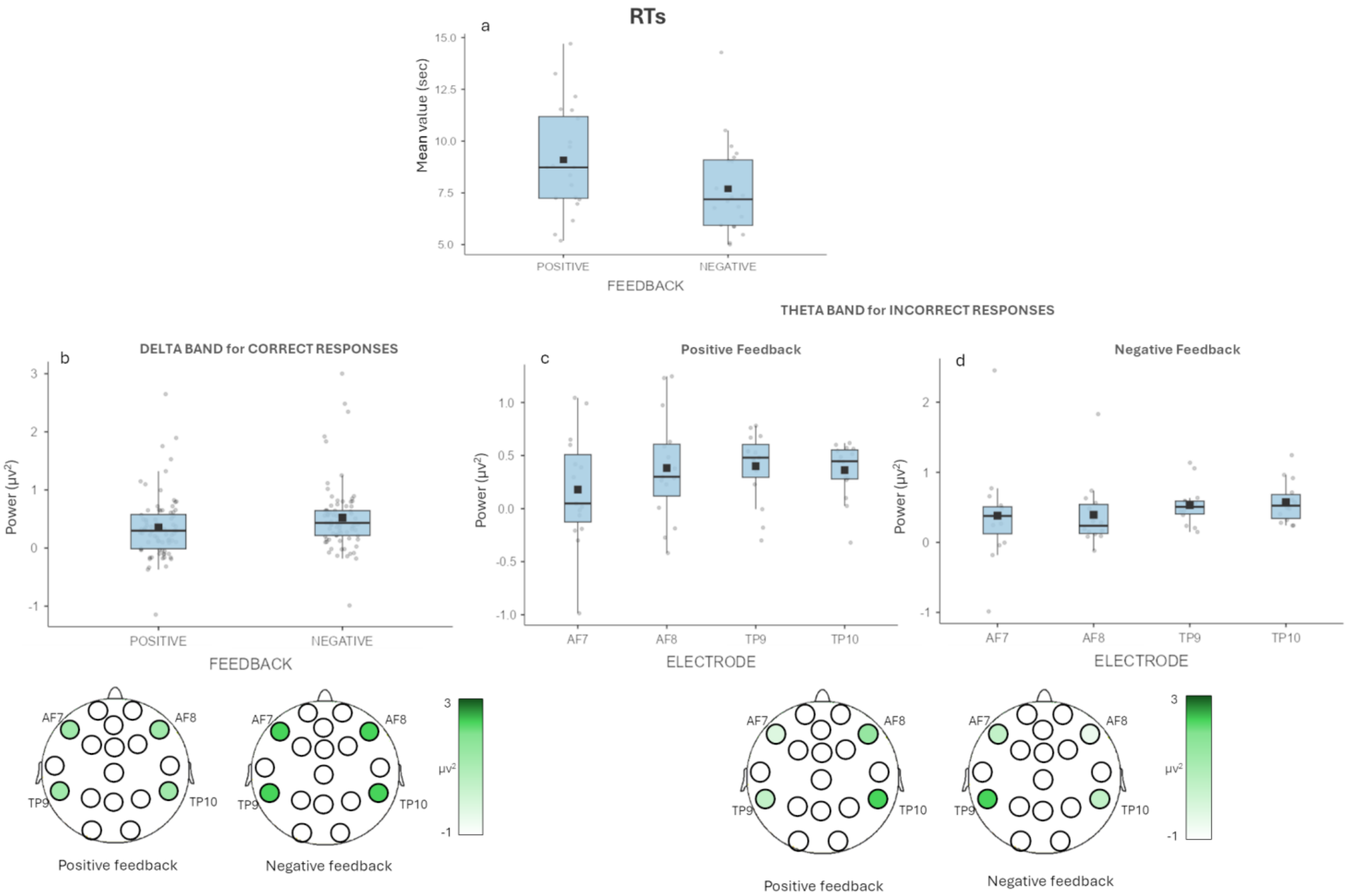

Figure 11. Behavioral results and EEG results for delta and theta. (a) The graph shows significant differences for RTs with higher RTs in the recall of the decisions with positive feedback compared to those with negative feedback. (b) The graph shows significant differences for correctly recalled decisions for delta band in feedback. The figure under the graph is a graphic representation of the differences in delta activity during the recall task for positive and negative feedback decisions. (c-d) The graph shows non-significant differences in multiple comparison correction for wrongly recalled decisions for theta band in *Feedback* × *Electrode*. For each graph bars represent ±1 se and dots represent observed score.

2.2.2 EEG results

2.2.2.1 Delta band

A main effect for Feedback was found [$F(1,19) = 13.225$, $p = 0.002$, $\eta^2 = 0.022$], with higher mean values of delta band for the correct recall of the decisions that in the first phase (i.e., the decision-making phase) received negative feedback ($M = 0.523$, SE = 0.071) compared to those that received a positive feedback ($M = 0.354$, SE = 0.064) (Figure 11b).

No other significant effects were found (all $p > 0.05$). No significant differences were found for wrongly recalled decisions (all $p > 0.05$).

2.2.2.2 Theta band

A significant interaction effect Feedback × Electrode was found [$F(3,33) = 4.818$, $p = 0.007$, $\eta^2 = 0.026$] for the wrongly recalled decisions. In the post-hoc investigating the interaction effect showed: slightly higher values for AF7 for recalled decisions with negative feedback ($M = 0.391$, SE = 0.231) compared to those with positive feedback ($M = 0.180$, SE = 0.145); for AF8 for recalled decisions with positive feedback ($M = 0.432$, SE = 0.112) compared to those with negative feedback ($M = 0.296$, SE = 0.074); for TP9 for recalled decisions with negative feedback ($M = 0.541$, SE = 0.088) compared to those with positive feedback ($M = 0.404$, SE = 0.078) and for TP10 for recalled decisions with negative feedback ($M = 0.561$, SE = 0.084) compared to those with positive feedback ($M = 0.410$, SE = 0.056), but none of them survived multiple comparison correction (Figures 11c,d).

No other significant effects were found (all $p > 0.05$). No significant differences were found for correctly recalled decisions (all $p > 0.05$).

2.2.2.3 Alpha band

Concerning correctly recalled decisions, a main effect for Electrode [$F(3, 57) = 9.456$, $p = <0.001$, $\eta^2 = 0.268$] was detected. Pairwise comparisons revealed higher mean values for alpha band in TP9 ($M = 1.078$, SE = 0.075, $p = 0.009$) and TP10 ($M = 1.178$, SE = 0.103, $p = 0.007$) compared to AF7 ($M = 1.178$, SE = 0.103), and in TP10 compared to AF8 ($M = 0.630$, SE = 0.120, $p = 0.011$) (Figure 12a).

About wrongly recalled decisions, we observed the same main effect for Electrode [$F(3,33) = 9.99$, $p = <0.001$, $\eta^2 = 0.374$]. Pairwise comparisons revealed higher values for alpha band in TP9 ($M = 1.092$, SE = 0.104, $p = 0.035$) and TP10 ($M = 1.143$, SE = 0.103, $p = 0.012$) compared to AF7 ($M = 0.400$, SE = 0.160), and in TP10 compared to AF8 ($M = 0.621$, SE = 0.083, $p = 0.046$) (Figure 12b).

Also, it was found a significant interaction effect Feedback × Electrode [$F(3,33) = 4.86$, $p = 0.007$, $\eta^2 = 0.008$]. Pairwise comparison showed higher mean values for alpha band in TP10 ($M = 1.202$, SE = 0.125) compared to AF7 ($M = 0.442$, SE = 0.161) for wrongly recalled decisions with negative feedback ($p = 0.029$) (Figure 12c).

No other significant effects were found (all $p > 0.05$).

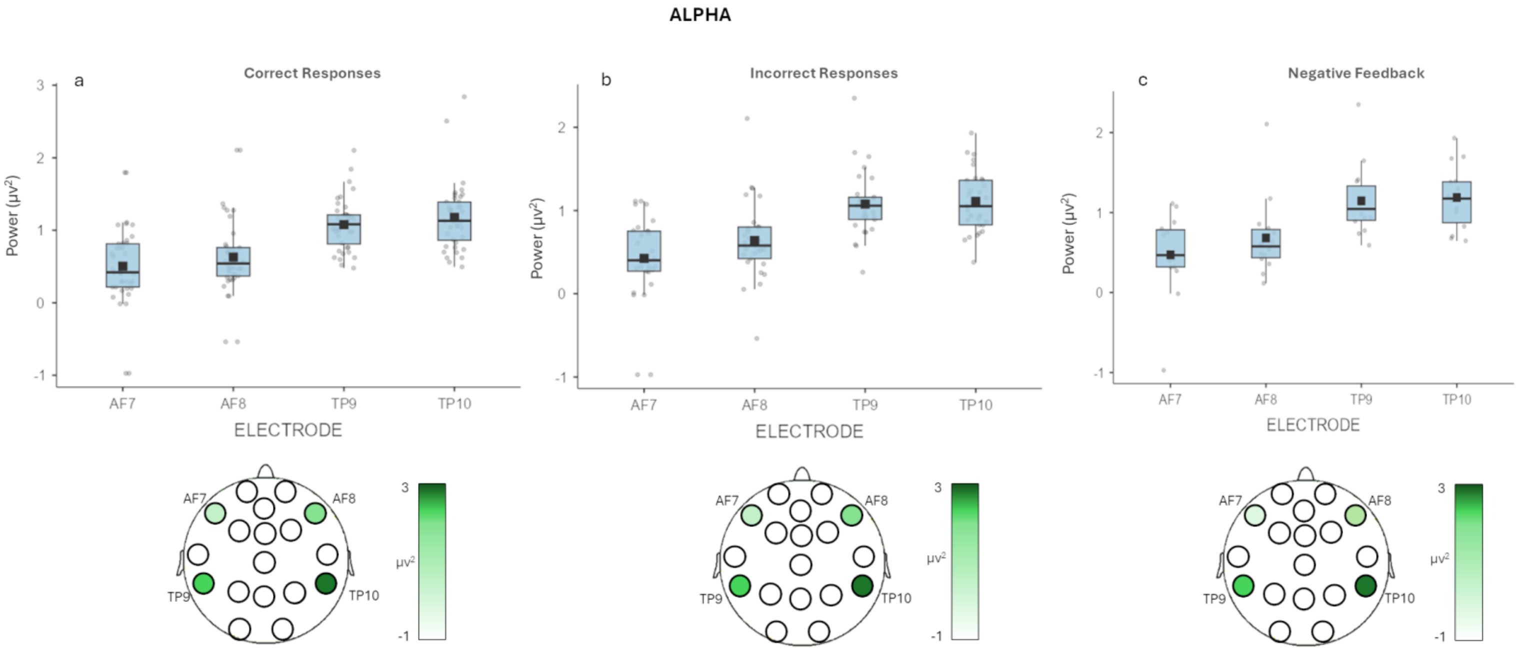

Figure 12. EEG alpha band results. (a) The graph shows significant differences for alpha band for correctly recalled decisions in *Electrode*. Bars represent ±1 SE and dots represent observed score. (b) The graph shows significant differences for alpha band for wrongly recalled decisions in *Electrode*. The figure under each graph is a graphic representation of the brain area involved during the recall task. Bars represent ±1 SE and dots represent observed score. (c) The graph shows significant differences in multiple comparison correction for alpha band in *Feedback* × *Electrode*. Bars represent ±1 standard error and dots represent observed score. The figure under the graph is a graphic representation of the differences in alpha activity during the recall task for negative feedback decisions.

2.2.2.4 Beta band

For beta band, it was detected a main effect for Feedback [$F(1,19) = 8.09$, $p = 0.002$, $\eta^2 = 0.005$], with higher mean values of beta band for wrongly recalled decisions with a negative ($M = 0.685$, SE = 0.087) compared to positive feedback ($M = 0.608$, SE = 0.086) (Figure 13a).

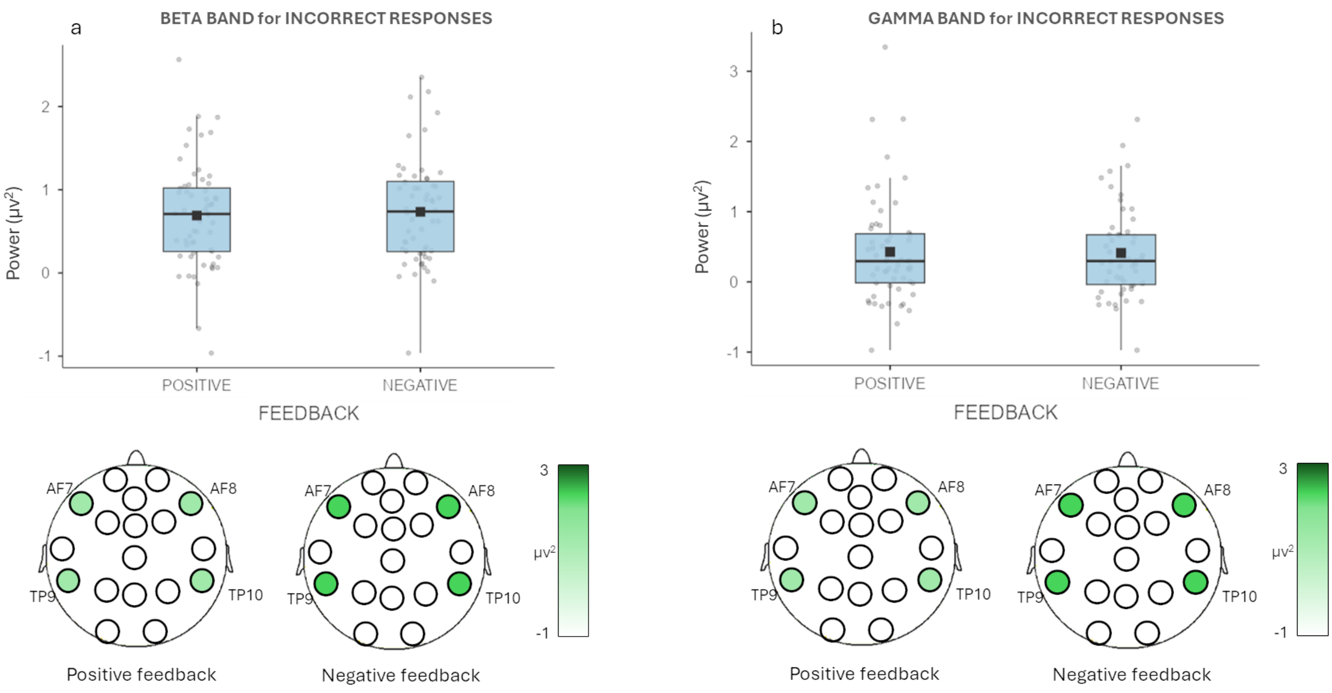

Figure 13. EEG beta and gamma bands results. (a) The graph shows significant differences for wrongly recalled decisions for beta band in feedback. Bars represent ±1 se and dots represent observed score. (b) The graph shows significant differences for wrongly recalled decisions for gamma band in feedback. Bars represent ±1 SE and dots represent observed score. The figure under each graph is a graphic representation of the differences in beta and gamma activity during the recall task for positive and negative feedback decisions.

2.2.2.5 Gamma band

Regarding gamma band, a main effect for Feedback [$F(1,19) = 7.272$, $p = 0.022$, $\eta^2 = 0.003$], with higher mean values of gamma band for wrongly recalled decisions with a negative ($M = 0.362$, SE = 0.105) compared to positive feedback ($M = 0.291$, SE = 0.111) (Figure 13b).

No other significant effects were found (all $p > 0.05$). No significant differences were found for correctly recalled decisions (all $p > 0.05$).

2.3 Discussion

The present study examined behavioral – specifically ACC, ERRs and RTs – and EEG data in a sample of decision-makers when recalling prior decisions under two feedback conditions (positive *versus* negative).

Behavioral results only showed higher RTs for accurately recalled decisions with positive feedback compared to those with negative feedback. These results might suggest that attentional biases toward positive information can impact cognitive processing and memory retrieval (Thoern et al., 2016) . This influence may result in slower recall times for positive information compared to negative stimuli. Another possible interpretation addressed by García-Arch et al. (2024) is that people tend to prefer receiving feedback that aligns with their self-representation, suggesting that they actively utilize self-consistent information to reinforce self-identity, which may help maintain the stability of self-concept. Nonetheless, we might speculate that decisions with negative feedback are easier to recall since people are more likely to prioritize negative over positive information across various psychological contexts (Norris et al., 2019) . Besides, results showed no significant differences in recall accuracy. Indeed, we might speculate that since participants were healthy individuals with typical performance levels, their ACC probably reached a ceiling effect, showing no significant differences across conditions. However, more sensitive measures, including RTs – which are indicators of cognitive effort and decision workload (Balconi, Acconito, et al., 2024) – and EEG, revealed distinctions between correct and incorrect responses, offering deeper insights into the underlying neural processes.

Regarding EEG results, analysis showed as expected for both correctly and wrongly recalled decisions a general decrease of alpha band mainly in frontal areas (AF7, AF8) compared to temporo-parietal areas (TP9, TP10) in the recall of decisions despite feedback valence. Alpha oscillations indeed function as a gatekeeper in neural processes, playing a crucial role in directing attention and accessing stored information during tasks by managing cognitive load via the inhibition of distractions (Knyazev, 2013). Specifically, suppression of alpha band activity in frontal areas supports top-down control, aiding working memory and attention by filtering distractions and enhancing focus, particularly during recall tasks (Payne et al., 2013; Zanto et al., 2011). In contrast, temporo-parietal alpha activity is associated with memory encoding and maintenance, with higher alpha power improving memory performance (Kimura et al., 2016). Interestingly, results showed low level of alpha band in AF7 compared to TP10 for wrongly recalled decisions with negative feedback suggesting that while frontal areas attempt to control and focus attention, right temporoparietal processing [that might be marked by the right-temporoparietal junction – rTPJ – an area associate with attentional process (Carter & Huettel, 2013; Corbetta & Shulman, 2002)] remains insufficient for accurate recall, especially under conditions of negative feedback that threaten self-concept and may be processed more superficially. Indeed, this pattern of activation could reflect an interaction between the need for self-concept stability and the selective disengagement of attention from self-incongruent feedback, limiting the effective integration of such information (García-Arch et al., 2025).

Conversely, results showed higher delta band activity for correctly recalled decisions with negative compared to positive feedback. Notably, this result is consistent with findings that associate delta oscillations with aversive states, thus episodes linked to positive emotions showed a more pronounced decrease in delta power, while those linked to negative emotions displayed an increase in delta power (Knyazev et al., 2015). Additionally, it is worth noting that delta-increased activity is generalized to the whole scalp and not localized to a specific brain area, which underlines the role of this EEG band in processing and recalling negative stimuli (Allegretta et al., 2024; Balconi et al., 2009; Knyazev et al., 2015) .

Regarding wrongly recalled decisions, results showed the implication of high frequency bands beta and gamma. Indeed, analysis showed an increase of beta and gamma for wrongly recalled decisions with negative feedback compared to positive ones. Notably, beta plays a crucial role in supporting top-down control processes in retrieving information from memory (Miller et al., 2018). Additionally, findings show that a decrease in beta power is associated with successful memory formation, particularly in the left inferior prefrontal cortex (Hanslmayr et al., 2011). The modulation of beta oscillations during memory tasks seems connected to encoding and recall processes, with beta wave desynchronization correlating with improved memory performance (Hanslmayr et al., 2014). Furthermore, research shows that beta band activity reflects the cognitive load linked to recalling negative memories, with higher beta power associated with more effortful retrieval processes (Shin et al., 2017) . This might indicates that increased beta activity may serve as a neural marker for the cognitive effort needed to access negative memories or alternatively – as shown by findings from ERP studies – where beta-related top-down control and P300 amplitude modulation are tied to valence and expectancy effects (Paul et al., 2022), suggesting that the increased beta activity observed here could signify heightened cognitive effort to process the recall of unexpected negative feedback incongruent with one's self-representation. Furthermore, similarly to delta, beta did not show significant increase over a specific brain area: indeed, as found by Crespo-García et al. (2022) upon detecting unwanted memories, not a specific area, but several brain areas are engaged (including the anterior-cingulate cortex and the hippocampus) through specific neural oscillatory patterns, thus beta and theta bands.

Notably, it is worth mentioning that theta showed a significant feedback-dependent modulation of electrodes' activity for the wrongly recalled decisions, showing a generalized higher activity for decisions with negative feedback compared to those with positive feedback in AF7, TP9 and TP10, that however did not survive multiple comparison correction. As highlighted by Crespo-García et al. (2022) theta oscillations in the dorsal anterior cingulate cortex play a crucial role in activating inhibitory control by the right dorsolateral prefrontal cortex during motivated forgetting. Thus, in the case of this study, it is possible that theta signals memory suppression indicating greater control demands for cognitive conflict resolution (Sauseng et al., 2019). However, this speculation might be better addressed by using a high-density EEG in future research.

On the other hand, gamma is associated with encoding and retrieval of specific memory traces, helping the improvement of the accuracy of recalled information (Lundqvist et al., 2016) . Research suggests that beta-gamma activity also acts as a "motivational value signal" (HajiHosseini et al., 2012) and increases with heightened attentional resources toward significant events driving behavioral adjustments when feedback is relevant (Li et al., 2016). Therefore, we might speculate that the increased activity of both beta and gamma when wrongly recalling decisions with negative feedback might be interpreted as a neural marker indicating a motivational signal that is perceived as a treat to the self and that therefore prompts a selective forgetting of that self-threatening negative feedback. This speculation might be supported by the MNE (Sedikides & Green, 2004, 2006) which posits that individuals are motivated to protect and enhance their positive self-concept, causing them to process negative, self-threatening feedback less thoroughly. This shallow processing creates fewer memory retrieval pathways, leading to weaker recall of decisions with such feedback. Nonetheless, this selective forgetting might underline a certain level of awareness of the subject in avoiding the recall of a negative event, perceived as self-threatening. Interestingly, as pointed out by Balconi, Angioletti, et al. (2023) self-awareness is associated with heightened activity in both the gamma and beta bands, suggesting a synergistic relationship between these oscillations in supporting this process.

Nonetheless, recent studies (García-Arch et al., 2024, 2025) might offer an alternative explanation to the findings of the current study: notably, the differing behavioral and neural responses triggered by recalling a decision that received positive or negative feedback may also be attributed to how well the feedback aligns with the existing self-concept. As pointed out by the authors, self-concept characteristics support psychological continuity and may protect self-representations from being rapidly altered by self-incongruent information (Conway, 2005; Nowak et al., 2000), therefore identity-discrepant inputs are identified early in the processing stages and classified as "false" information (Abendroth et al., 2022). This suggests that the swift detection of self-incongruent feedback serves to safeguard self-representations from disruption by subjectively inaccurate information. Overall, this study reveals key behavioral and EEG factors in recalling decisions under different feedback conditions. Behaviorally, accurate recalls with positive feedback showed longer RTs, likely due to an attentional bias toward positive information (Thoern et al., 2016). Regarding electrophysiological data, reduced alpha activity in frontal areas during both correct and incorrect recalls supports the role of alpha oscillations in managing cognitive load (Knyazev, 2013). Correct recalls with negative feedback showed increased delta activity, linked to aversive states (Knyazev et al., 2015), while incorrect recalls with negative feedback exhibited higher beta and gamma activity, suggesting cognitive effort in processing self-threatening feedback (Miller et al., 2018). This study highlights how feedback valence shapes recall accuracy, RTs, and neural oscillations. However, it is worth mentioning that the positivity bias might be one of different interpretations of the current results. Indeed, as pointed out by García-Arch et al. (2024) in a recent study, there is in healthy adults a behavioral tendency to prioritize the assimilation of feedback that aligns with one's self-perceptions over feedback that contradicts them. This aligns with the idea that self-beliefs are deeply integrated within a complex network of autobiographical memories, which require stabilizing mechanisms to maintain self-representations and resist contradictory information (Conway, 2005; Nowak et al., 2000). From this perspective, the need to maintain self-concept stability and coherence acts as a strong constraint, influencing which external information is processed and retained, with a preference for information perceived as self-congruent (García-Arch et al., 2025). Therefore, the role of valence may be more complex and potentially secondary to other factors, such as self-congruence, particularly in healthy adult populations. This suggests that the alignment of feedback with self-perceptions could exert a stronger influence on behavioral and neural responses than the mere positive or negative nature of the feedback itself (García-Arch et al., 2024).

While this study is innovative in its multi-method approach to examining the recall of previously made decisions based on feedback valence by integrating behavioral and EEG data, it has some limitations. The primary limitation is its small sample size, which may affect the statistical power of the findings. Future research with a larger participant pool is recommended to validate these results. Moreover, future studies with larger sample size should consider the application of advanced EEG analyses approach using data-driven tests, such as cluster-based permutation test. Secondly, using a wearable EEG device presents limitations: indeed, even if it offers ecological validity, easy setup, and greater comfort with dry electrodes (Acabchuk et al., 2021; Ratti et al., 2017), they also have drawbacks, such as limited scalp coverage, which restricts the examination of broader neural networks (Cannard et al., 2012; Zhang & Cui, 2022). Future studies could improve accuracy and reduce artefacts by using high-density EEG, allowing for more comprehensive mapping of cortical activity related to these processes. Furthermore, future studies could delve deeper into these findings, by incorporating psychometric data through self-report measures examining how individual factors, such as personality traits, decision-making style and maximization tendencies relate to variations in behavioral performance and EEG activity. Another important limitation of the present study is the omission of EEG data collected during the feedback phase. Indeed, these neurophysiological data would have allowed us to associate the brain activity and behavioral patterns observed during recall to processes occurring in the feedback phase, therefore providing a more comprehensive understanding of the mechanisms underlying recall. By focusing solely on the outcomes of the recall phase, our findings are limited to describing the results relative to the recall phase rather than the dynamic processes leading to them. Future studies should consider integrating feedback-related data to enable a more comprehensive analysis of recall and its associated neural and behavioral patterns. Finally, to gain a comprehensive understanding of the implicit components of decision-making, a neuroscientific approach that combines behavioral data with EEG and autonomic measures would be valuable. This approach could clarify the neurophysiological and autonomic responses involved in the recall process, offering insights into cognitive effort and emotional engagement. Moreover, comparing neurophysiological and autonomic responses between the decision-making and recall phases could reveal key differences in processing across these stages.

Chapter 3 – Study 2: Cognitive flexibility and adaptive behavior: the role of feedback in situated decision-making[2]

3.1 Introduction

In an effort to better understand the relationship between a person's characteristics and the processes leading him/her to make a decision, research on decision-making has largely relied on the construct of decisional style, understood as a "learned habitual response pattern exhibited by an individual when confronted with a decision situation […] not a personality trait, but a habit-based propensity to react in a certain way in a specific decision context" (Scott & Bruce, 1995, p. 820). This perspective has led to the development of models where decisional styles are deemed as primary predictors for the development and outcomes of individual decisional processes (Curşeu & Schruijer, 2012; Scott & Bruce, 1995; Thunholm, 2004) . In one of the best-known of these models, Scott & Bruce (1995) identified five different decisional styles: rational, intuitive, dependent, avoidant, and spontaneous.

Decisional processes are not solely a consequence of an individual's past experience and learned habits. From a perspective that highlights the situated and embodied determinants of human cognition (Wilson, 2002) , here we focus on situated aspects of decision-making, and on the relationship between decisional processes, the situation in which the decision takes place, and decision-makers' representation of such situation (Balconi, 2023; Crivelli, 2023). Decision-making is often driven and guided by the evaluation of action effects and external cues on action outcomes, which are essential to adaptively optimize behavior (Cohen et al., 2007) , and depending on whether they are positive/favourable or negative/unfavourable. Decisional behavior is indeed shaped and, often improved, by interactions with the environment in two different ways (Cunillera et al., 2012):

[2] This paper can be found at the following bibliographic reference: Crivelli, D., Allegretta, R.A. & Balconi, M. (2023). The "status quo bias" in Response to External Feedback in Decision-Makers. *Adaptive Human Behavior and Physiology*, *9*, 426–441. https://doi.org/10.1007/s40750-023-00230-1

when positive/negative environmental signals suggest that a decisional strategy needs to be modified and that it is time to switch to a new set of rules for processing incoming stimuli (rule-based behavioral adjustment); or when these cues are used to confirm (or disconfirm) if an action was effective (outcome-based behavioral adjustment).

An individual's sensitivity to positive/negative cues and to feedback on decision outcomes, as well as the effectiveness in evaluating and strategically using such information, are known to be influenced by personal characteristics, such as mental health (Balconi et al., 2022; Crivelli, Balena, et al., 2024), anxiety levels (Giorgetta et al., 2012), moral principles (Boyd, 2006), adherence to social norms (Balconi et al., 2019), impulsivity (Völlm et al., 2007) , and responsiveness to rewards (Scheres & Sanfey, 2006). As an example, anxious individuals tend to react less positively to favourable feedbacks on their choices (e.g., gains) but also less negatively to unfavourable feedbacks (e.g., losses), and show reduced tendency to change their choices after negative feedback than non-anxious individuals (Giorgetta et al., 2012).

High-level metacognitive executive functions – which include planning, problem-solving, working memory, and performance monitoring – are a component of the capacity to employ environmental signals in a flexible way (Balconi et al., 2020; Cunillera et al., 2012; Diamond, 2013). Brand et al. (2006) model of decision-making under objective risk conditions also highlights the central role of executive functions. According to this model, in order to organize pertinent information, evaluate the options, and manage the application of strategies, executive functions are required. Cognitive flexibility is an important factor in the decision-making process in the organization field, in which rigidity in making strategic decisions might have serious negative repercussions (Sharfman & Jr, 1997). Cognitive flexibility – understood as the ability to change the mode of operation according to situational factors and feedback and to consequently match cognitive processing strategies with the specifics of task at hand (Laureiro-Martínez & Brusoni, 2018) – is considered essential to overcome the so-called cognitive inertia, namely an excessive dependence on particular mental models that limits an individual's or an organization's capacity to recognize and respond to changes (Hodgkinson, 1997; Hodgkinson & Wright, 2002).

The expression of cognitive flexibility often depends on two main factors: identification of many facets, viewpoints, and perspectives on an ongoing decisional scenario, and active processing and reasoning on such aspects in order to detect potential connections and to appraise them (Diamond, 2013; Raes et al., 2011). The development of such recursive process is, then, further informed and shaped by environmental cues concerning the effect, efficacy, and implications of the choices made by the decision-maker.

To better understand the effects of their choices, individuals thus need external feedbacks, which according to Brand et al. (2006) are processed via two routes – the emotional and cognitive route – in line with dual-processing theories (Evans, 2008; Kahneman, 2003; Reyna, 2004). In theory, both pathways can respond to feedback and be activated simultaneously.

The emotional route - in keeping with embodied models of social-cognitive skills (Pace-Schott et al., 2019) and, more specifically, of decisional skills (Loewenstein et al., 2001; Morelli et al., 2022) – modulates peripheral body reactions and somatic activity (e.g., increased heart rate, visceral reactions, perspiration, etc.) in response to both the occurrence of previously selected options that led to negative outcomes and to the decisional process itself. Such physiological modulations, in turn, inform the decisional process and help shaping its development together with subjective affects and emotional experiences during exposure to the decisional situation (Crivelli, Allegretta, et al., 2024).

In the cognitive route, environmental cues and feedback-related data are strategically used to appraise and re-evaluate strategies. Furthermore, executive control mechanisms support ongoing monitoring and reiterated conscious access to those pieces of information to verify the success of current decision-making approach and to check and possibly adjust the strategy based on their positive/favourable vs. negative/unfavourable connotations.

The common substrates for such self-monitoring, cognitive-affective regulation, information integration, and appraisal processes are the prefrontal areas of the brain. Medial structures in prefrontal cortices, such as the anterior cingulate cortex (ACC), in particular, play a pivotal role in situated decision-making since they are implicated in monitoring actions and their outcomes to adjust subsequent behavior. This also results in an increase in cognitive control, presumably through the increased recruitment of lateral prefrontal areas when an action or its outcome is not consistent with expectations and active action inferences, and medial structures thus signal the need for corrections and alternative solutions to be evaluated or implemented (Kerns, 2006; Kerns et al., 2004; Ridderinkhof et al., 2004). The dorsolateral prefrontal cortex (dlPFC) may integrate information over time and adjust higher-level decision-making techniques to changing situations and demands (Lee & Seo, 2007; McClure et al., 2004; Tanaka et al., 2006).

Studies investigating the involvement of these prefrontal structures have shown that medial frontal EEG power for the theta band and related intertrial phase coherence increase after mistakes or unfavourable performance feedback more than after successful trials or favourable feedback. According to Cavanagh et al. (2009) and Cavanagh & Frank (2014), frontal oscillatory theta-band activity also predicts post-error slowing and post-correct speeding as well as model-derived prediction mistakes. Theta-band oscillations in the frontal network, therefore, seem to be engaged in transmitting affective-laden error messages and implementing both task-specific and task-general adaptations when internal or external cues signal an unsatisfactory outcome and, therefore, the need to adjust behavior (Vijver et al., 2011). In contrast, EEG power for the beta band was observed to increase in association to feedback providing the subject with useful information for situated learning, such as a financial gain or a successful response in a learning scenario (Cohen et al., 2007). This is also consistent with the hypothesis that increases in beta-band activity support current motor or cognitive processes through management of workload, endogenous top-down regulation of attention and, generally, mental resources (Bastos et al., 2015; Engel & Fries, 2010; Michalareas et al., 2016; Wróbel, 2000). Nonetheless, it must be noted that such EEG data, while highly valuable, still primarily derive from studies based on simple or abstract tasks. It remains unclear whether the conclusions of these studies can be extrapolated to the domain of realistic and complex decision-making.

This study aimed at investigating individuals' sensitivity to positive/favorable and negative/unfavorable feedback and their flexibility in changing a previously made decision following that feedback in realistic decision-making scenarios. In addition, we explored how brain frequencies changed during the time window in which people decided to confirm or change their choice after the received feedback. Such measures can complement behavioral assessment with relevant information on neurofunctional markers and their modulations linked to feedback valence and cognitive engagement. This study also investigated possible correlations between decision-making styles – as defined by the Scott and Bruce model and evaluated through the General Decision Making Style (GDMS) inventory (Gambetti et al., 2008; Scott & Bruce, 1995) – and decision-making flexibility depending on feedback valence.

We hypothesized that, at the behavioral level, there would be a tendency to adjust previous decisions when receiving negative feedback from the environment compared to the tendency to stay with one's own decisions when receiving a positive reinforcement. As for the neurofunctional markers, we expected lower frontal beta activity when participants are presented with environmental cues that reinforce previous choices and do not prompt behavioral adjustment. Further, we expected greater beta activity during the review phase when no feedback is provided, reflecting greater cognitive engagement when considering whether or not to change a previous choice while no clues are available. If the distress associated with receiving negative feedback is so consistent as to affect individuals even beyond its receipt and processing, we could observe increased theta activity during the related review phase, reflecting emotional engagement and regulation of distress. Finally, we hypothesized that there may be a negative correlation between Dependent scores on the GDMS – typical of those who strongly rely on advice and suggestions from others in decision-making – and task scores reflecting individuals' tendencies to maintain their own decisions.

3.2 Materials and Methods

3.2.1 Sample

Sixty-one participants (age: M = 34.57, SD = 11.54; 21 males, 40 females) took part in the study. An a priori power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the minimum sample size required to test the study hypotheses. Results indicated the required sample size to achieve 80% power for detecting a medium effect ($f = 0.25$), at a significance criterion of $\alpha = 0.05$, was N = 28 for repeated-measures ANOVA with three measurements and one group. Accounting for a potential attrition rate of 30%, the minimum required sample size would be N = 36. Thus, the obtained sample size of N = 61 is adequate to test the study hypotheses. Recruitment was conducted via consecutive sampling. No compensation was provided for study participation.

Inclusion criteria were: age > 18 years; normal or corrected-to-normal vision and hearing. Exclusion criteria were: history of psychiatric or neurology disorders, severe head trauma, and/or stroke; ongoing therapy based on psychoactive drugs that could alter cognitive or decisional skills; clinically relevant condition of distress; experience of stressful life events in the last 6 month.

None of participants reported a history of psychiatric or neurology disorders. None of them was receiving treatment with psychoactive drugs that could alter cognitive or decisional skills. Finally, none of them showed clinically relevant signs of distress or reported recent stressful life events. All of participants had normal or corrected-to-normal vision.

The study experimental procedures and methods comply with the standards and principles of the Declaration of Helsinki and were approved by the Ethics Committee of the Department of Psychology, Catholic University of the Sacred Heart. Written informed consent to participate in the study was obtained from each participant.

3.2.2 Procedure

Participants were led to a quiet testing room, where they were they were asked to wear a wearable dry EEG system and then introduced to the experimental setting, procedures, and task instructions.

On average, experimental sessions lasted 30 min, including the dry-EEG montage and the filling in of psychometric tests. In order to minimize potential situational confounds, the experimental sessions were conducted by certified psychologists with experience in experimental research and/or psychodiagnostics.

The experimental task was digitalized and administered via an experiment-management platform. The task is designed to investigate the situated decision-making process, with a specific focus on the cues the context provides to the decision-maker regarding the outcomes of his/her decisions (positive or negative reinforcements). Specifically, participants are presented with a realistic professional scenario in which they are asked to make a decision (see Supplementary Materials for an example of the realistic decision-making scenarios). After making their decision, participants may receive feedback on the option they choose. Feedbacks were conditional and could serve as positive or negative reinforcers (see Supplementary Materials for an example of reinforcer for one of realistic decision-making scenarios). After being presented (or not) with feedbacks on their choices, participants were presented with the opportunity to review their choices, and change them. Participants, then, could choose between further decisional alternatives (see Supplementary Materials for an example of final alternatives). Based on the option selected by participants after being presented with the general scenario, each alternative presented in the final step of the task was given a score, ranging from 1 to 5; participants were thus evaluated on their decisional behavior in relation to the situation and to contextual cues. Participants obtained higher scores when they remained consistent in their decisions or when they flexibly adjusted their expectations and decisions following a positive or a negative reinforcement from the social context. The decisional scenarios had been previously validated by independent judges, who rated their ecological and construct validity, as well as their realism, intelligibility, and clarity.

In addition to the experimental task, participants were asked to fill in the General Decision Making Style (GDMS) inventory (Scott & Bruce, 1995). Such inventory was devised to assess individual decisional styles based on a model including five different profiles – labelled as Rational, Intuitive, Dependent, Avoidant, and Spontaneous – which describe primary attitudes towards decision-making. The Rational style is characterized by a comprehensive and exhaustive search for information, considering all alternatives and their consequences before choosing. The Intuitive style is defined by a focus on details and a tendency to make decisions based on hunches. The Dependent style identifies a person who prefers to receive suggestions and external support when facing decisions. The Avoidant style defines a person who tends to avoid making decisions. Finally, the Spontaneous style is typical of those who seek immediacy and are driven by the desire to quickly conclude the decisional process. Each of the five profile constitutes a specific dimension of the construct of decisional style and is measured via a 5-item subscale. Responses are collected by using five-point Likert scales.

3.2.3 EEG data acquisition and analysis

EEG data were collected via a wearable dry-EEG system (MuseTM headband, version 2; InteraXon Inc, Toronto, ON, Canada). In this system, four electrodes are positioned in the prefrontal (AF7 and AF8) and temporoparietal (TP9 and TP10) areas, while three medial frontopolar electrodes are utilized as a reference. The frontal and temporoparietal electrodes of the Muse headband are positioned in accordance with the 10 International System for electrode placement (Chatrian et al., 1985) and they are made of conductive material and silicon rubber, respectively.

Data are captured and transmitted to a connected smartphone app via Bluetooth, using the Mind Monitor's mobile application. A constant 256 Hz sampling rate was used for data collection and a 50 Hz notch frequency filter was applied. Participants were asked to keep their eye blinks and movements to a minimum. Frequency components of EEG signals were extracted via an automated FFT algorithm to compute power density values for standard EEG bands (delta, theta, alpha, beta, gamma). Subsequent analyses focused on theta and beta EEG bands due to their functional interpretation. Theta power was chosen due to its association with error processing, affective arousal and emotion regulation (Cavanagh & Frank, 2014; Ertl et al., 2013; Korotkova et al., 2018), while beta power is considered a marker of cognitive processing, workload, and focus on a task (Engel & Fries, 2010; Wróbel, 2000). Average power density value of the theta and beta bands over prefrontal areas were specifically computed for the final phase of the task in which, after being presented (or not) with feedbacks on their choices, participants were presented with the opportunity to review their choices. Such computation was performed for each experimental condition: no feedback (NoF), positive feedback (PF), and negative feedback (NF).

3.2.4 Data analysis

Behavioral (scores at the final phase of the task) and EEG data (power density values for the theta and beta frequency bands, as described above) were first analysed through repeated-measure ANOVA including Condition (NoF, PF, and NF) as within-subject independent factor. Type-I Errors due to inhomogeneity of variances were controlled for by applying Greenhouse-Geisser correction to the degrees of freedom when needed, based on results of Mauchly's test. Pair-wise comparisons were used to further explore statistically significant main effects. In order to account for multiple comparisons bias, Bonferroni corrections to probability values were applied while computing pair-wise comparisons. Partial eta squared (η^2) was computed to assess the size of significant effects. Effect sizes were deemed as small when $|0.10| \leq \eta^2 < |0.25|$, medium when $|0.25| \leq \eta^2 < |0.40|$, and large when $\eta^2 \geq |0.40|$, in agreement with Cohen's norms (1988). Threshold for statistical significance was set to $\alpha = 0.05$.

As a control analysis to rule out potential confounds related to gender-related differences in behavioral responses or electrophysiological measures, *t*-tests including gender (male vs. female) as an independent factor and behavioral and EEG data as dependent measures were also performed. Statistical significance was set to $\alpha = 0.05$.

To further explore potential associations between behavioral and psychometric (GDMS scores) data, we also performed correlation analyses. We computed Pearson correlation coefficients (ρ) between the behavioral response at the task and subscale scores of the GDMS, taking into account experimental conditions – i.e., NoF, PF, and NF. For correlations, effect sizes were deemed as small when $|0.10| \leq \rho < |0.30|$, medium when $|0.30| \leq \rho < |0.50|$, and large when $\rho \geq |0.50|$, in agreement with Cohen's norms (1988). Threshold for statistical significance was set to $\alpha = 0.05$.

3.3 Results

The ANOVA model on task scores highlighted a statistically significant main effect of Condition ($F[2, 120] = 15.779$, $p < .001$, $\eta^2 = 0.72$). Pair-wise comparisons revealed significantly lower task scores following NF than NoF ($p < .001$) and PF ($p < .001$), with MNF = 2.07 (95% CI [1.85, 2.28]), MNoF = 4.08 (95% CI [3.93, 4.24]), and MPF = 4.21 (95% CI [4.01, 4.41]; see Fig. 14).

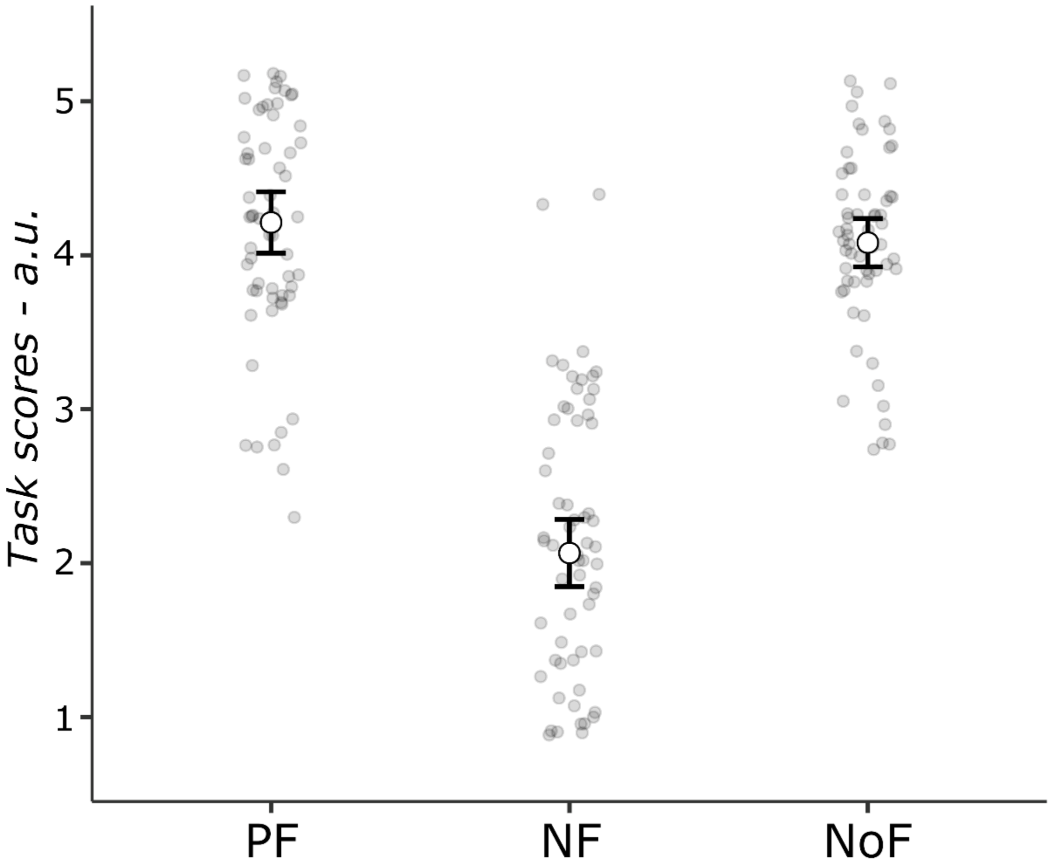

Figure 14. Distribution of task scores across experimental conditions: positive feedback (PF), negative feedback (NF), and no feedback (NoF). The white dots represent mean values, grey dots represent individual values, bars represent the 95% confidence interval.

The models run on theta power density values did not highlight any significant differences.

Finally, the ANOVA model on beta power density values revealed a statistically significant main effect of Condition ($F[2, 100] = 4.111$, $p = .026$, $\eta^2 = 0.08$). Pair-wise comparisons highlighted significantly lower beta values during the review phase following positive feedback with respect to the one in the no-feedback condition ($p = .020$), with MPF = 3.17 (95% CI [2.70, 3.65]), MNF = 3.48 (95% CI [2.93, 4.02]), and MNoF = 3.72 (95% CI [3.07, 4.37]; see Fig. 15).

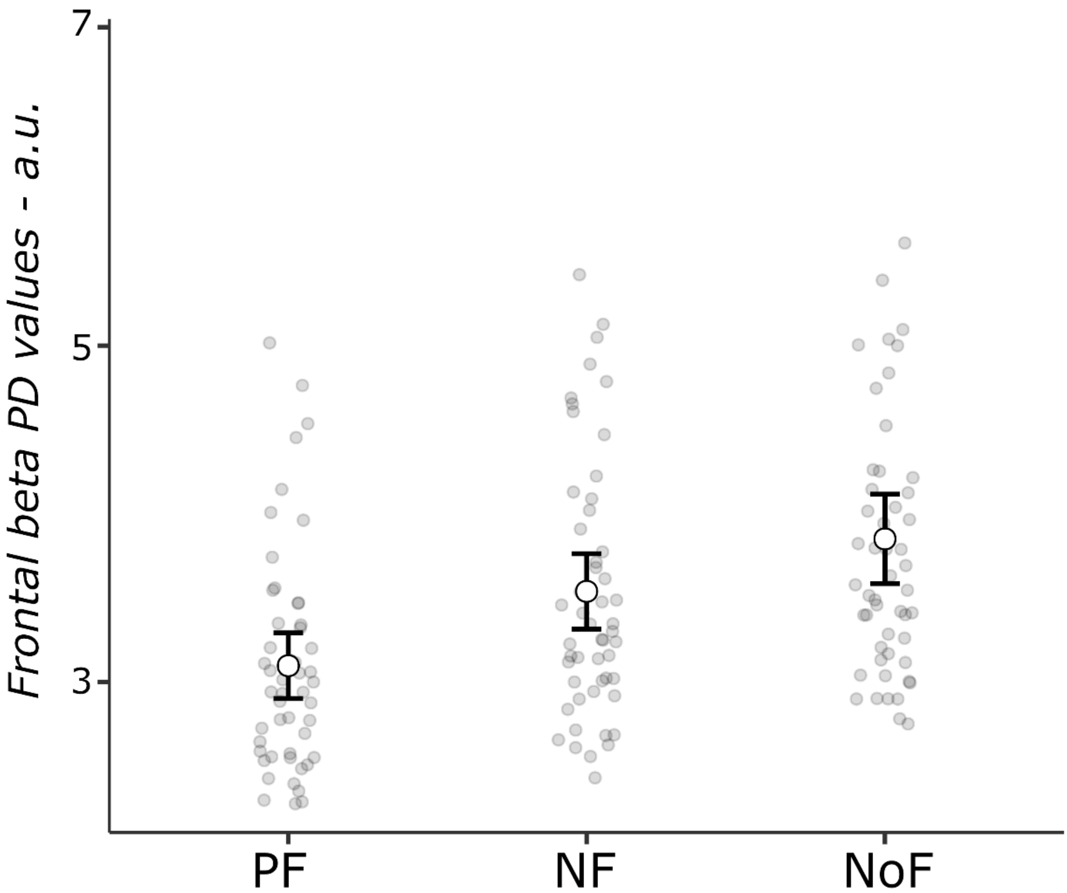

Figure 15. Distribution of frontal beta power density values across experimental conditions: positive feedback (PF), negative feedback (NF), and no feedback (NoF). The white dots represent mean values, grey dots represent individual values, bars represent the 95% confidence interval.

Control analyses (*t*-tests) included to rule out potential gender-related confounds did not highlight any statistically significant effects.

We found statistically significant negative correlations between the Dependent scores on the GDMS and task scores in the positive feedback ($\rho = -0.365$, p = .004) and no-feedback ($\rho = -0.323$, p = .012) conditions. In addition, a positive statistically significant correlation was found between Spontaneous scores at the GDMS and task scores in no-feedback condition (ρ = 0.258, p = .047).

3.4 Discussion

Our study produced three main results: (i) participants showed a greater tendency to keep their decisions in the face of a reinforcing feedback or when no explicit feedback was provided; some of them tended to maintain their decision also following negative feedback; (ii) participants showed lower cognitive effort, as marked by lower prefrontal beta power, during the decisional review phase following positive feedback compared to when no feedback was available, with intermediate levels of cognitive effort following negative reinforcers; (iii) we found negative correlations between GDMS Dependent style scores and task scores in the positive feedback and no-feedback conditions; we also found a positive correlation between GDMS Spontaneous style scores and task scores in the no-feedback condition.

The first finding partly supports our first hypothesis. As predicted, we observed a clear tendency to stay the chosen course when receiving a positive reinforcement, as marked by high task scores following positive feedbacks. As for the reappraisal phase following negative feedback, in partial disagreement with our expectations, we observed – on average – a tendency to reaffirm previously made decisions when receiving negative feedback from the environment. This pattern, along with the observed stability of decisions in the absence of external cues concerning their consequences, might suggest a general orientation towards cognitive conservatism, perhaps sustained by need for consistency, and independent from the type and quality (positive or negative) of external feedback. We suggest that this might be interpreted as an expression of a "status quo bias". Building on previous attempts to explain why people remain committed to their decisions (and even sustain them by providing more resources when they have not been successful), Samuelson & Zeckhauser (1988) first introduced the concept of status quo bias to describe individuals who, given the choice of doing nothing versus changing, choose to do nothing. Real-life examples of such bias are the resistance to divestment in finance or ordering the same food repeatedly in a known restaurant instead of taking a risk on a new (tough potentially tastier) option. Interestingly, in their observations, the effect was even more prevalent when the decision was a salient and important one. The status quo bias has been widely investigated in consumer choices (Chernev, 2004; Yen & Chuang, 2008), decision-making (Burmeister & Schade, 2007; Eidelman et al., 2009; Maner et al., 2007), and general organizational inertia (Boyer & Robert, 2006; Gal, 2006; Gibbons & O'Brien, 2001).

The status quo bias may provide individuals with the opportunity to feel good about their previous decisions and increase the perception of their own effectiveness (Samuelson & Zeckhauser, 1988; Staw, 1981). The suggestion that this bias is about self-image (Silver & Mitchell, 1990) has led to new research on inter-individual differences in its manifestation. As an example, Gibbons & O'Brien (2001) found that the background of the decision maker (e.g., professional experience, international work experience, and multiplicity of operational background) modulates the tendency to express the status quo bias. Moreover, Chernev (2004) found that the promotion vs. prevention orientation of a consumer affects the occurrence of a status quo bias in their decisional processes.

The occurrence of marked individual differences in the manifestation of the status quo bias resonates with our observation of high variability in participants' task scores, especially when related to the negative feedback condition, for which they ranged from 1 to 4 on a five-point Likert scale and that showed interquartile range (IQR) equal to 2 out of 4. Whether individuals keep or change their decisions may depend on the availability of environmental cues on decision consequences, but their own predispositions may play a stronger role when they receive a feedback that might explicitly question their previous decisions. In such situations, and in particular individuals, staying the course in decision-making might represent an effort to reduce negative emotions tied to bad decisions or reduce anticipatory regret (C. J. Anderson, 2003). Consistent with the suggested connection between felt emotions and status quo bias, a previous study reported that incidental positive affect increased the bias toward the status quo (Yen & Chuang, 2008). Such interpretation seems further supported by our present neurofunctional findings.

We observed lower prefrontal beta power during the decisional review phase following positive feedback, i.e., a condition in which external cues reinforce previous choices instead of suggesting the need for a cognitive remodulation or reappraisal to assess alternative solutions. The observed pattern of lower prefrontal beta power following positive feedback and gradually increasing beta power values as participants are exposed to negative reinforcers or no feedback at all seems to suggest the occurrence of situated learning and decision-making processes. Indeed, beta EEG component is commonly deemed as a marker of task-oriented attention focusing and cognitive processing, as well as of top-down regulation of cognitive resources (Bastos et al., 2015; Engel & Fries, 2010; Michalareas et al., 2016; Wróbel, 2000). The fact that such physiological marker of workload is higher when no external cue is available to support recursive reviewing and appraisal processes on one's own choices than when such processes seem not needed, or when cognitive reappraisal is prompted by feedback highlighting unsuccessful consequences of previous choices, might plausibly reflect the involvement of higher cognitive executive functions and strategic reasoning to counterfactually assess alternatives and promote learning from experience. Interestingly, consistent with dual-processing theories of human cognition (Brand et al., 2006; Evans, 2008; Kahneman, 2003; Reyna, 2004), this could reflect the predominant contribution of the cognitive route in processing environmental and, when present, feedback-related information. Moreover, greater beta activity in the no-feedback condition than in the positive-feedback one points to the practical implications of giving and considering feedbacks, since situations in which feedback is not available are more cognitively demanding.

The lack of significant modulations of prefrontal theta power in the negative-feedback condition may suggest that the decisional reviewing phase as we implemented it has primarily evoked cognitive appraisal processes for assessment of alternative solutions, learning, and future-oriented planning instead of error monitoring and affective regulation processes to manage feedback-related distress. Such interpretation seems supported by the fact that evidence linking theta power increases to error monitoring and negative feedbacks was mainly provided by studies focusing on simple, exact, and clear feedbacks, primarily associated with errors or losses in motor/cognitive or gambling tasks (Balconi & Crivelli, 2010; Cohen et al., 2007; Holroyd & Coles, 2002; Luu et al., 2004). In contrast, the present experimental task uses realistic and complex decision-making scenarios, asking participants to reason on a choice they actually made and, after receiving (or not) feedback on the consequences of their decision, to evaluate whether or not to revise it. The greater complexity of the task used in our study and of the feedbacks provided to the participants limits the extent to which our present results can be directly compared with available findings on electrophysiological signatures of negative feedback processing. Although the use of complex scenarios and complex feedback might account for the above-noted negative finding, it may also suggest an involvement of the emotional route across the realistic decisional tasks. This possibility needs to be further explored and tested. For example, future studies could employ experimental conditions in which feedback is manipulated in terms of intensity, besides valence. Again, the role of individual metacognitive and self-regulation skills as protective factors against mental effort and distress associated with receiving negative feedback will likely be a crucial topic for future investigations (Balconi, Acconito, et al., 2023).

The negative correlation between task scores in the positive-feedback and no-feedback conditions and GDMS Dependent style scores is consistent with our expectations. The dependent style is, indeed, characterized by the relevance – for the decisional process – given to advice, support, and suggestions provided by others, and by a clear reliance on such external contributions. The fact that the tendency to maintain one's own decisions when no external cue is provided or when reinforcing cue are present increases as the presence of a dependent decisional style lowers hints at the potential modulatory role of a field independent cognitive style that might be worth additional investigation. Interestingly, dependent style score was found to correlate with external locus of control (Scott & Bruce, 1995). The positive correlation between the spontaneous decisional style and the tendency to maintain one's own decisions when no external cue is provided seems consistent with such a perspective. Indeed, the spontaneous style is characterized by a feeling of immediacy and the desire to quickly come through the decision-making process. Such approach to decision-making might reflect a general cognitively independent and self-confident style. This tentative interpretation should be further investigated by future research.

To sum up, the results of the present study highlighted the importance of receiving feedback, especially when positive or reinforcing, considering the cognitive effort required in the no-feedback condition compared to the feedback conditions as demonstrated by higher beta activity. Furthermore, they also suggested that sometimes even tough it could be critical, because this feedback may be too stressful, or because adjusting behavior in response to negative feedback is too costly. This finding might have important implications not only in a classical learning context, such as school or university, but also in the workplace, where the importance of feedback serves as a compass to orient one's own job performance and it is also useful to promote organizational well-being, and prevent and overcome the so-called cognitive inertia (Hodgkinson, 1997; Hodgkinson & Wright, 2002). Future research should focus on strategies to improve the ability to manage and adaptively use external feedback, such as via cost-benefit analyses. When the costs of change (psychological, social, energetic, cognitive costs) are too high, inertia may become the chosen option. Knowing such phenomenon, being able to detect it and recognize it, and having access to effective defensive or contrasting strategies working on cognitive or affective mechanisms influencing decision-making represent crucial competences for both professional decision-makers and lay people.

Further research with larger cohorts is needed and replication of our results using different samples would strengthen our data interpretation. First, future studies should take into account age differences by testing feedback sensitivity across lifespan using realistic scenarios. Second, it might be of particular interest for applied researchers to investigate how decision-making processes, flexibility and feedback sensitivity are influenced and change among different firm cultures. Finally, an additional challenge for the future might be to study the relationship between decisional flexibility, compliance among the decision-maker's social network, and self-criticism as a trait, in order to further investigate the expression of adaptive and strategic use of external feedbacks to guide one's own decision-making strategy.

3.5 Supplementary Materials

Example of a realistic decision-making scenario:

"The possibility has arisen in your company to offer employees training on digitalisation. You are in a period of intense work and several projects will have to be completed shortly to be presented in some tenders. On the other hand, you believe the course is useful and important. What do you do?

a) I accept the training course for the team, it is an investment that could pay off over time

b) I refuse the training course for the team, there is already a lot to do at the moment and a commitment of this type could slow down and put at risk the delivery of projects".

Example of positive reinforcers for one of realistic decision-making scenarios:

"Choice A: Thanks to the training course, team members learned to use some programs that allowed them to automate and innovate some aspects of the projects they were working on. This also streamlined the workload required to finish projects, so you managed to finish all the projects to be submitted on time.

Choice B: You still managed to complete all the projects you had planned. This makes you very proud and satisfied as it shows that your team was sufficiently prepared from a technological point of view to adequately tackle the projects carried out."

Example of final alternatives for one of realistic decision-making scenarios:

A. I would choose not to take the course in any case

B. I would tend to choose not to take the course, provided that the situation still leads me to think I am up to the task

C. Next time I'll evaluate based on what the context suggests

D. I would tend to choose to take the course because it is always useful to enrich knowledge and skills

E. I would choose to take the course again anyway"

Chapter 4 – Study 3: Metacognitive regulation of strategic planning: from Executive Functions to self-awareness[3]

4.1 Introduction

The ability to develop awareness of one's strategic plan adopted during an action, to reflect on one's performance, as well as to distinguish between right and wrong decisions and outcomes is known as metacognition and is crucial for functional decision-making processes. The regulation of the decision-making process is significantly impacted not only by the high-order executive functions (EFs) of selecting, planning, updating, and changing behaviors but also by the metacognitive awareness of having planned an appropriate action strategy (knowledge about cognition) and monitoring one's strategy (monitoring of one's cognition) (Flavell, 1979; Whitebread et al., 2009). These two metacognitive components (the knowledge about cognition and monitoring of one's cognition) that have been mentioned in several models of metacognition (Flavell, 1979; Schraw et al., 2006) are crucial for decision-making process. They primarily activate prefrontal brain regions, which are the basis of EFs as well as higher-order processes involved in learning and self-awareness (Cleeremans et al., 2007; Fleming, 2023).

Indeed, EFs comprise a family of functions (including working memory, planning, flexibility, and inhibitory control) that are necessary for formulating goals, planning how to achieve them, and carrying out those plans effectively (Lezak, 1982), whilst metacognition is placed at a higher-level order and encompasses both the level of awareness of individual's executive functioning (such as being aware of the identification and selection of appropriate strategies that guided the decision-making process), that the evaluation and control of one's strategy to guide the decisional behavior.

[3] This paper can be found at the following bibliographic reference: Balconi, M., Allegretta, R. A., & Angioletti, L. (2025). Metacognition of one's strategic planning in decision-making: the contribution of EEG correlates and individual differences. *Cognitive Neurodynamics*, *19*(1), 4.

Concerning the function of planning, it is necessary to make a conceptual distinction "within" such function, since the implementation of strategic planning can be considered a component of EF, while the awareness, evaluation, and control of the adopted strategic plan can be considered as a metacognitive process (Foster & Skehan, 1996).

Therefore, executive planning constitutes the basis of a strategic planning action. The control and awareness of strategic planning constitutes a "first-level" of metacognition. While being aware of this metacognitive control over strategic planning implies a "second-level" of metacognition, which does not simply coincide with the two metacognitive components of knowledge of cognition and monitoring of one's cognition mentioned above, but involves knowing how to use awareness mechanisms to better regulate the present or future action execution: this ability has been here conceived as the "metacognition of one's planning strategy" (Angioletti et al., 2020; Balconi et al., 2014, 2015; Balconi & Campanella, 2021). So far, the relation between decision-making process and this metacognition ability of one's strategic planning has been little explored.

On the one hand, a classic example of neuropsychological task that has been used for decades to measure EFs, decision-making, and strategic planning in healthy and clinical samples is the Towers of Hanoi (TOH) task (Goel & Grafman, 1995; Griebling et al., 2010; Shuai et al., 2017; Slomine et al., 2002; Yu et al., 2016); on the other hand, self-report measures have been previously exploited to collect information on which strategy individuals used to complete a decision-making task.

With reference to the TOH task, in this task, a predetermined number of disks must be moved from a starting setup to a target display in the fewest number of movements (Liang et al., 2016). For successfully completing the TOH task, different EFs are required, such as the planning of actions and processes for attaining a specific goal (Lezak et al., 2012), decision-making, the use of short-term memory, the execution of a plan in compliance with a set of guidelines (Schuepbach et al., 2002; Welsh & Huizinga, 2001) and the capacity to switch between mental sets with flexibility (Bull et al., 2004).

Prior studies using TOH have all shown the Prefrontal Cortex (PFC) activity in the anterior, inferior, and dorsolateral regions (Kaller et al., 2011; Ruocco et al., 2014). Additionally, a higher task complexity (i.e., a higher number of movements required to reach the target state) resulted in higher neural activity levels, especially in the left dorsolateral area of the PFC (DLPFC). While the right DLPFC has been linked to mental processes and working memory, the left DLPFC has been linked to the identification of information pertinent to the goal and the development of an internal problem representation (Ruocco et al., 2014).

Furthermore, the PFC's activation during the computerized version of TOH has been demonstrated through the use of various neuroimaging methods including functional Magnetic Resonance Imaging (fMRI) (Crescentini et al., 2012; Griebling et al., 2010; Head et al., 2002) and electroencephalogram (EEG) (Guevara et al., 2013; Ruiz-Díaz et al., 2012). A recent pilot neuroimaging study demonstrated the DLPFC activation related to the planning process during the long-time learning of the TOH (Mitani et al., 2022). Also, Guevara et al. (2013) demonstrated that during the performance of the TOH task, young adults and adults display an EEG pattern characterized by an increase in the delta band in all brain derivations, interpreted as a marker of concentration processes (Harmony et al., 1996) and decision-making (Başar et al., 2001) linked to efficient task performance, and a decrease in alpha band in frontal and parietal areas, associated with greater vigilance and attention (Mulholland, 1972; Ray & Cole, 1985a) during the TOH performance. Although Guevara et al. (2013) has the merit to deepen EEG cortical oscillations in relation to the TOH task, they also stated they lack information on which strategy the participants used to complete the task and did not include a measurement of metacognition in their experiment.

On the other hand, several questionnaires have been developed to assess metacognitive skills and different facets of metacognition in a variety of fields of application (Fleming & Lau, 2014; Gascoine et al., 2017). In general, in metacognition research, two established instruments exist: a broader Metacognitive Awareness Inventory (MAI; Gregory & Sperling 1994) consisting of metacognitive knowledge and metacognitive regulation scales, and a shorter, single-factorial

Metacognitive Self-Regulation scale from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al. 1993) that measures planning, metacognitive monitoring, and metacognitive regulation during learning. To make the assessment of metacognition more agile, studies in other contexts have previously selected reduced number of items or subscales of these metacognitive scales to administer (Taasoobshirazi & Farley, 2013) . Otherwise, a different approach has been frequently adopted in the context of decision-making, which consisted of asking participants to perform a behavioral task and to estimate the confidence in their choices (e.g., post-decision wagering; Brevers et al., 2013; Kepecs & Mainen, 2012) that in the end will be correlated with objective performance (Fleming, 2023).

A halfway solution consists of proposing the execution of a behavioral task followed by the request to fill in a limited set of items developed to measure an individual's awareness of decision and strategic planning during the task performance. In line with this approach, we have recently demonstrated in a series of studies within the clinical field of addiction, that the objective performance at a decision-making task (Iowa Gambling Task, IGT) correlates with metacognitive dimensions measured with single items assessing the ability to adopt planning a strategy, the strategy awareness, the ability to adopt a flexible strategy and the sense of efficacy (Balconi et al., 2014, 2015).

However, to the best of our knowledge, no previous research measured through a multi-level neuroscientific approach the relation between TOH performance correlates (behavioral and EEG markers) and metacognitive abilities. Notably, to the best of our knowledge, no former studies focused on the so-called "second-level" of metacognition, which is here defined as the awareness of metacognitive control over strategic planning, thereby distinguished from the "first-level" of metacognition, understood as the control and awareness of strategic planning during a decision-making task. The "second-level" of metacognition – or as previously defined the "metacognition of one's planning strategy" – is here intended as a process that entails acquiring the ability to use mechanisms of awareness to regulate the execution of present or forthcoming actions more effectively. Therefore, to fill the current gap in the literature, it proves necessary to investigate and focus on this “second level” of metacognition through a multi-level neuroscientific approach, integrating behavioural data acquired from the TOH task and EEG performance correlates.

In addition, it should be noted that individual differences, like personality profiles and decision-making styles, have been associated both to the performance at decision-making tasks and to metacognition levels (Basu & Dixit, 2022; Colombo et al., 2010). Buelow & Cayton (2020) found that a higher Big Five Agreeableness personality score was associated with less risky decisions at the IGT. Basu & Dixit (2022) demonstrated that the metacognitive component of knowledge about cognition was positively associated with intuitive and spontaneous decision-making styles, while the metacognitive regulation of cognition emerged to be positively related to rational decision-making style. Therefore, it could be speculated that individual differences (in terms of personality profiles and decision-making styles) could be linked to metacognition and perhaps also differentiate between the different components and levels of metacognition. However, the relationship between individual profiles and behavioral and metacognitive performance has not yet been explored in depth in the literature, specifically regarding the “second-level” of metacognition.

Based on these assumptions, this work aims to test the relationship between the behavioral and EEG correlates of strategic planning abilities, measured with a modified version of the TOH task, the “metacognition of one’s planning strategy”, and individual differences in personality profiles and decision-making styles.

To do so, during the TOH task, the behavioral and electrophysiological (EEG frequency bands: delta, theta, alpha and beta band) data were collected to obtain both a behavioral *Planning Performance* index [based on the completed levels and reaction times (RTs) at the TOH task] and EEG indices of cognitive effort and control needed to develop the strategic plan and executing it efficiently.

After the task, a metacognitive scale was applied to measure participants’ metacognition on the task (Angioletti et al., 2020; Balconi et al., 2014, 2015), through 5 items assessing specifically the global use of strategic planning (item 1), the strategy awareness during the task (item 2) strategy changes across levels (item 3), participants' perception of having used a successful strategy (item 4), the willingness to change strategy a posteriori (item 5).

Also, to assess individual differences in personality profiles and decision-making styles, three psychometric scales were used in the current study: the 10-item Big Five Inventory (10-item BFI) (Guido et al., 2015), which allows for highlighting five specific personality profiles: extroversion, agreeableness, conscientiousness, emotional stability, and open-mindedness; the General Decision-Making Style scale (GDMS; Scott & Bruce, 1995), which proposes five different independent decision styles (rational, intuitive, avoidant, dependent, and spontaneous); and the Maximization Scale (MS; Nenkov et al., 2008), which include three main dimensions characterizing a decision-maker, that are the tendency to hold high standards, to seek better alternatives and the difficulty in deciding.

Given these premises, it was hypothesized to find a positive correlation between the TOH *Planning Performance* index and the items of the metacognition scale, since better behavioral performance is expected to correlate with higher metacognition scores.

Secondly, it was supposed a positive correlation between the willingness to change the strategy a posteriori (measured with the item 5 score) and EEG delta increase and alpha decrease in left DLPFC during task performance (according to Guevara et al., 2013; Ruocco et al., 2014), as a marker of a relation between executive planning and higher metacognition of one's strategic planning.

Thirdly, concerning the relation between metacognitive items and individual personality profiles and decision-making styles, it was expected to observe a positive correlation between the BFI Emotional Stability subscale and the first four metacognitive items, since this personality profile is characterized by confidence and the ability to deal better with challenging situations; and, a negative correlation between the GDMS intuitive subscale and item 5, because individuals with this decision-making style tend to decide on the basis of their first intuition without the perspective to change their decision a posteriori. Also, other potential associations between individual differences and metacognition measures are expected.

Finally, it was also hypothesized a potential relation between individual differences (personality profiles and decision-making styles) and the performance during the task (both behavioral performance and EEG pattern). Indeed, it is expected to observe a positive correlation between three main individuals' profiles characterized by the tendency to be organized, make decisions based on careful considerations (Gambetti et al., 2008), hold high standards for themselves and things in general, that are BFI Conscientiousness subscale scores, GDMS Rational style and MS High Standards and TOH planning behavioral *Planning Performance* index. As well as a positive correlation between these three profiles and the higher presence of EEG delta band in the left DLPFC, as a marker of executive planning during task performance is expected.

4.2 Methods

4.2.1 Sample

The sample recruited for the current study included 24 participants (age: Mean = 35.33, Standard Deviation = 11.94; 13 males, 11 females) without any specific area of professional specialization. To determine the minimum required sample size, we performed an a priori power analysis correlations (Bivariate normal model). Results showed that, in order to detect a significant correlation, a minimum sample size of 23, with an alpha error probability of 0.05 and a power of 0.80, was required for a large effect (G*Power 3.1 software, Heinrich-Heine, Germany).The exclusion criteria included: traumatic head injury and/or ictus, clinically significant distress and depression, neurologic or psychiatric illness, ongoing therapy with psychoactive medications affecting cognition and decision-making assessed through a semi-structured interview. All participants were aged above 18 years old, healthy, right-handed, and had normal or corrected-to-normal vision and hearing, as well as no prior history of neurological or psychiatric disorders, learning disabilities, drug abuse, or chronic illness. Before participating in the study, each subject gave their written informed consent. No participant was familiar with the Tower of Hanoi (TOH) task before the study. Both the evaluation procedure and the study were designed in compliance with the revised Declaration of Helsinki (2013) and to the

GDPR - Reg. UE 2016/679 and its ethical guidelines. The research procedure was accepted by the ethics committee of the institution where the work was carried out.

4.2.2 Procedure

The whole experimental procedure took place in a quiet room dedicated to the experimental setting. Participants sat in a comfortable chair in front of a computer monitor placed at a distance of 80 centimeters. They all signed an informed consent and received full instructions on the experimental procedure. Then, the EEG wearable MUSE™ headband was applied to record their EEG activity for a total of 120 s resting state baseline. After the baseline, participants' EEG activity was constantly recorded during the performance of the computerized version of the TOH task. Participants were told that the TOH task performance would have been used to evaluate their ability to plan short- and long-term actions, as well as their decision-making skills, which prove necessary and valuable not only in everyday life, but also in the workplace where this competence is fundamental for one's professional growth. After the task, they were asked to think about their experience during the task and fill in a 5-item metacognitive scale (Balconi et al., 2014) through the following instructions: *"Now we ask you to think about your experience during the task and answer the following questions"*. After this procedural step, they were asked to fill in the following psychometric scales: the 10-item Big Five Inventory (Guido et al., 2015), the General Decision- Making Style (GDMS) inventory (Scott & Bruce, 1995), and the Maximization Scale (Nenkov et al., 2008). The whole experimental procedure lasted approximately 25 min. Figure 16 shows the experimental setup with the EEG wearable MUSE™ headband and the laboratory setting.

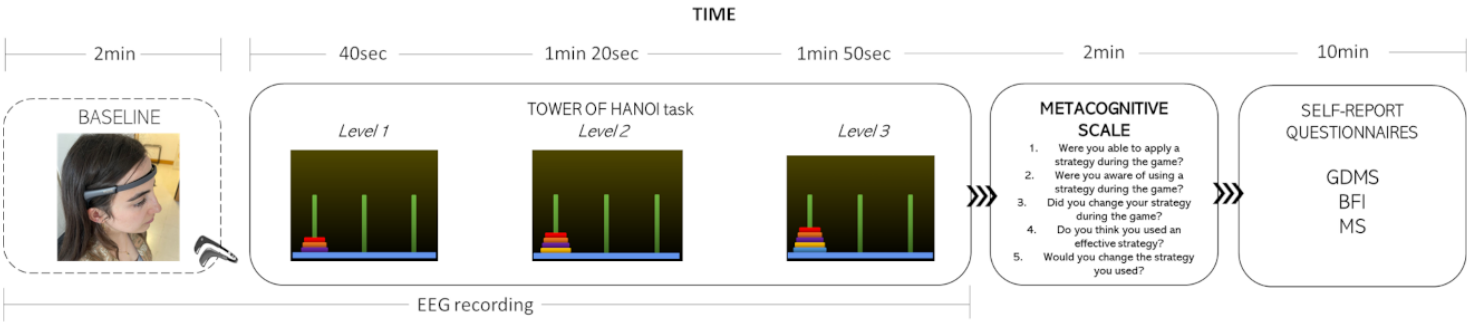

Figure 16. Display of the experimental procedure along the timeline. In the figure it is possible to observe how the Muse™ EEG wearable Device was applied to collect the EEG data from the resting state baseline (lasting 2 min) until the entire duration of the TOH task (lasting approximately 4 min). At the end of the task, sufficient time (about 12 min) was given to the participants for completing the metacognitive Scale and the self-report questionnaires to measure personality profiles and decision-making style.

4.2.3 Towers of Hanoi (TOH) task

In this study, a computerized version of the Towers of Hanoi task (administered through PsyToolkit, as an experiment-management platform; Stoet, 2010, 2017) consisting of 3 levels with increasing difficulty was adopted to assess participants' decision-making and planning abilities. Each level included an increasing number of disks (3, 4, and 5 disks) and a different time limit to complete the task (1st level: 40 s; 2nd level: 1 min and 20 s; 3rd level: 1 min and 50 s). Participants received the instruction that, for each level, the goal was to move the entire setup of the tower from the first peg to the third one. They were asked to move and respect the following two rules: *(i)* only the top disk of the peg can be moved during each move; (ii) a larger disk cannot be placed on top of a smaller disk. Participants were also warned that to solve the problem they needed to choose the strategy allowing them to reach their goal with the least number of moves. The following instructions were given to the participants:

"*At the bottom of the screen you will see 3 pegs with several discs of various sizes. Discs can be moved by grabbing them (mouse click and hold) and dragging them to a different peg. Releasing the disc will place it on the peg. Your goal is to move the entire setup from the first peg to the third by moving the disks.*

There are 2 rules to observe:

Move only the top disc a given peg

A larger disk cannot be placed on top of a smaller disk

There are several ways to solve the problem, try to find the strategy that allows you to reach the goal with the least number of moves possible!

When you're ready, press the button to start.".

During task performance, the following parameters were measured for each level: latency to the first movement, the total number of movements, number of incorrect movements, RTs, and level complete or incomplete.

The total number of completed levels (maximum score: 3) and the total time of execution for the 3 levels were translated offline as a metric scale ranging from 1 to 10, obtaining respectively a Planning Performance score (PPs) and an Execution Time of the Planning task score (ETPts). Then the two scores were computed to obtain a Planning Performance index (PlanPerf-i), that measures the ability to plan action in the short term and long term. Specifically, this index was obtained through a ratio between the Planning Performance score and the Execution Time of the Planning task score as follows: PlanPerf-i = PPs_{dec} / $ETPts_{dec}$.

4.2.4 Metacognitive measures

A modified version of the metacognitive scale of Balconi et al. (2014) was adopted in the current work to evaluate individuals' metacognitive understanding of the strategies applied during the task. The scale includes five items measuring different aspects of metacognition: the ability to plan a strategy, strategy awareness, the ability to adopt a flexible strategy, the sense of efficacy, and prospective reasoning. In particular, item 1 refers to the Global use of Strategic planning (GSP: "*Were you able to apply a strategy during the game?*"); item 2 measures Strategy Awareness during the task (SA: *"Were you aware of using a strategy during the game?"*); item 3 assess Strategy Changes across levels (SC: *"Did you change your strategy during the game?")*; item 4 refers to participants' Perception of having used a Successful Strategy (PSS: *"Do you think you used an effective strategy?")*; item 5 assess the Willingness to Change Strategy a posteriori (WCG: *"Would you change the strategy you used?").* Responses were provided using a 5-point Likert scale, ranging from 1 (totally disagree) to 5 (completely agree). The first four items of this scale measure a "first level" of metacognition and, in particular, item 1 (GSP) and item 4 (PSS) measure aspects related to the knowledge of cognition, while item 2 (SA) and item 3 (SC) measure aspects related to the monitoring of cognition. In this study, to investigate a "second level" of metacognition, namely the metacognition of one's planning, a fifth item has been added (WCG), which measures more directly the intention of changing a future action following a conscious reflection on the current performance.

4.2.5 Psychometric measures

In addition to the experimental task, participants were asked to fill in the Italian version of the 10-item Big Five Inventory scales (Guido et al., 2015), the Italian version of the General Decision-Making Style (GDMS) inventory (Gambetti et al., 2008; Scott & Bruce, 1995), and the Maximization Scale (Nenkov et al., 2008) to collect self-report data on individuals' decision-making styles and personality profiles.

10-item Big Five Inventory. This 10-item questionnaire allows for the measurement of five different personality profiles: extroversion, agreeableness, conscientiousness, emotional stability, and open-mindedness (Guido et al., 2015). The individual is asked to answer to each item that best characterizes his personality through a 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher mean scores indicate greater levels of one of the personality traits.

General Decision-Making Style inventory. Based on a model with five different profiles – Rational, Intuitive, Dependent, Avoidant, and Spontaneous – which could define attitudes toward decision-making, the GDMS inventory (Scott & Bruce, 1995) was developed to evaluate individual decisional styles, using a 5-item subscale. Each subscale represents a distinct aspect of the decisional style construct.

Maximization Scale. This 13-item scale investigates individuals' tendency to maximize their choice, or, on the contrary, to settle with an option considered sufficiently good according to their own criteria (Nenkov et al., 2008). The participant is asked to answer each item via a 7-point Likert-type scale, that allows one to measure decision makers' tendency: (i) to hold high standards for themselves and things in general (high standard subscale), (ii) to seek better options (alternative search subscale), (iii) to encounter difficulties in making a choice (decision difficulty subscale).

4.2.6 EEG data acquisition and analysis

EEG data were collected using a dry-EEG wearable equipment (Muse™ headband, version 2; InteraXon Inc, Toronto, ON, Canada). This system employs four electrodes to gather EEG signals from the prefrontal (AF7 and AF8) and temporoparietal (TP9 and TP10) regions, together with three medial frontopolar electrodes as a reference. The electrodes on the Muse headband are placed according to the 10/20 International System for electrode placement (Jasper 1958). This wearable recording system is equipped with four bipolar dry electrodes featuring gold-plated cups composed of conductive material (silver) and silicon rubber. Additionally, it incorporates an accelerometer, a gyroscope, and pulse oximetry. A thin layer of water was applied to the dry electrodes using a sponge to both the frontal metal sensor and the conductive silicone rubber mastoid sensors located behind the ears. This was done to reduce impedance and enhance signal quality.

Through Bluetooth transfer to a connected smartphone, the mobile app "Mind Monitor" was used to record and collect all the data. Data were collected at a fixed sampling rate of 256 Hz, and a 50 Hz notch frequency filter was used to process the data. For limiting the presence of artifacts, participants were told to keep their eye blinks and movements to a minimum during the whole experiment.

Concerning EEG data processing, the removal of artifacts (such as eye blinks, jaw clenching, and movements) was done through visual inspection of all the data (less than 1% of data was removed). Through the logarithm of the power spectral density of the raw EEG data from each chan-nel, raw data were processed by Mind Monitor and transformed by using a Fast Fourier Transform (FFT) into brain waves at various frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (7.5–13 Hz), beta (13–30 Hz), and gamma (30–44 Hz). The Power Spectral Density (PSD) obtained from Mind Monitor's EEG was between − 1 and + 1. The algorithm used is proprietary from Mind Monitor app and not shared. At the start of the experimental phase, a 120-second resting state baseline was recorded, and task-related EEG activity was then weighted over baseline values for each participant as follows:

$$TRPSD = ((PSD_{task} - PSD_{bl})/PSD_{bl})$$

where TRPSD represents task-related changes in power spectral values for each frequency band and each electrode site, PSD_{task} represents power spectral values for each frequency band and each electrode site, and PSD_{bl} represents power spectral values in eye-open baseline for each frequency band and each electrode site.

4.2.7 Data analysis

For the statistical analysis, IBM SPSS 29 (IBM Corp., Chicago, IL, USA) was used.

For EEG data, four repeated measures analyses of variance (ANOVAs) were separately applied to the dependent measure of frequency bands (delta, theta, alpha, beta). Analysis was carried out with the following within factor *Electrode* (4: AF7, AF8, TP9 and TP10). For all ANOVA tests, degrees of freedom were corrected by the Greenhouse–Geisser epsilon when appropriate. Simple effects for significant interactions were further checked via pairwise comparisons, and Bonferroni correction was used to reduce multiple comparison potential biases. The sizes of statistically significant effects have been estimated by computing eta squared (η2) indices. The threshold for statistical significance was set at $\alpha = 0.05$.

To explore the relation between the behavioral and EEG correlates of strategic planning abilities, the "metacognition of one's planning strategy", and individual differences in personality profiles and decision-making styles, the following step of correlational analyses were performed by computing Pearson correlation coefficients.

4.2.7.1 Step one - correlations between the behavioral index and metacognitive measures

First, to explore the potential relation between behavioral task performance and metacognition, a set of Pearson's correlations were performed between the PlanPerf-i derived from task performance and each item of the metacognition scale.

4.2.7.2 Step two - correlations between the metacognitive measures and EEG data

Secondly, to examine if a specific EEG pattern activated during the task execution supports the meta-cognition, the single items of the metacognition scale were separately correlated to EEG frequency bands (delta, theta, alpha, and beta band) for the four electrodes (AF7, AF8, TP9, TP10) recorded during task performance.

4.2.7.3 Step three - correlations between the psychometric data, metacognitive measures, and EEG data

Thirdly, to determine the relation between individuals' profiles and EEG pattern supporting TOH task performance and metacognition, each of the subscale's scores of the psychometric tests applied during the study (BFI, GDMS and MS) were separately correlated to the single items of the metacognition scale and EEG frequency bands for the four electrodes recorded during task performance.

4.2.7.4 Step four - correlations between the psychometric measures

Finally, to investigate potential relationships between personality profiles and decision-making styles, a set of correlational analyses was also applied between each of the subscale's scores of the psychometric tests applied during the study (BFI, GDMS, and MS).

4.3 Results

In this section, the results obtained from the different steps of the analyses are reported.

For descriptive purposes, it is reported that ANOVA tests did not yield any significant differences between electrodes for each frequency band (delta, theta, alpha and beta) (Fig. 17A-D).

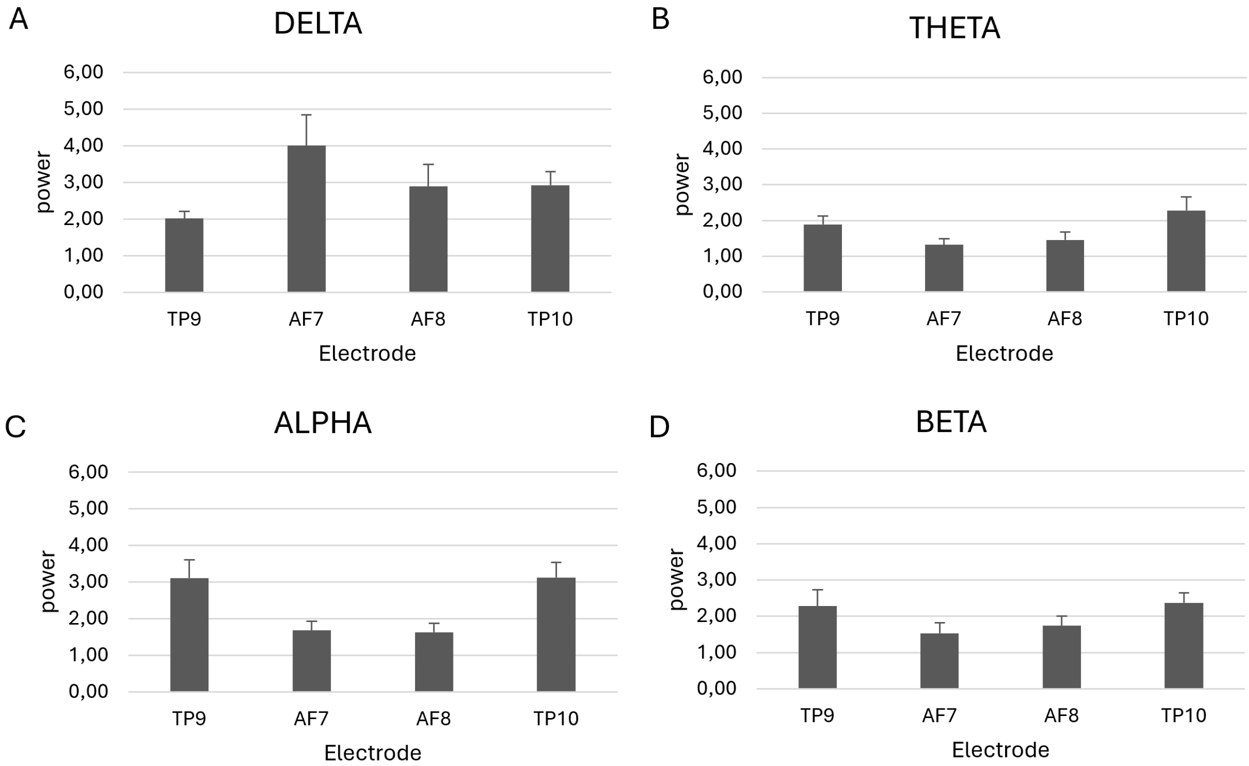

Figure 17. EEG data. The bar graphs display the mean PSD values for the following EEG frequency bands (A) delta band, (B) theta band, (C) alpha band, and (D) beta band. Bars represent the standard error (SE) of ± 1 for all plots.

4.3.7.1 Step one - correlations between the behavioral index and metacognitive measures

Correlations between the behavioral index *PlanPerf-i* and the single item of the metacognition scale yielded the following results. First, a positive correlation between the *PlanPerf-i* and GSP item was observed (r =.521, p =.011) (Fig. 18A) and PSS item (r =.539, p =.007) (Fig. 18B) was observed. Also, the *PlanPerf-i* negatively correlated with WCG item (r = −.407, p =.048) (Fig. 18C). No significant correlations were found between the behavioral index and SA and SC items.

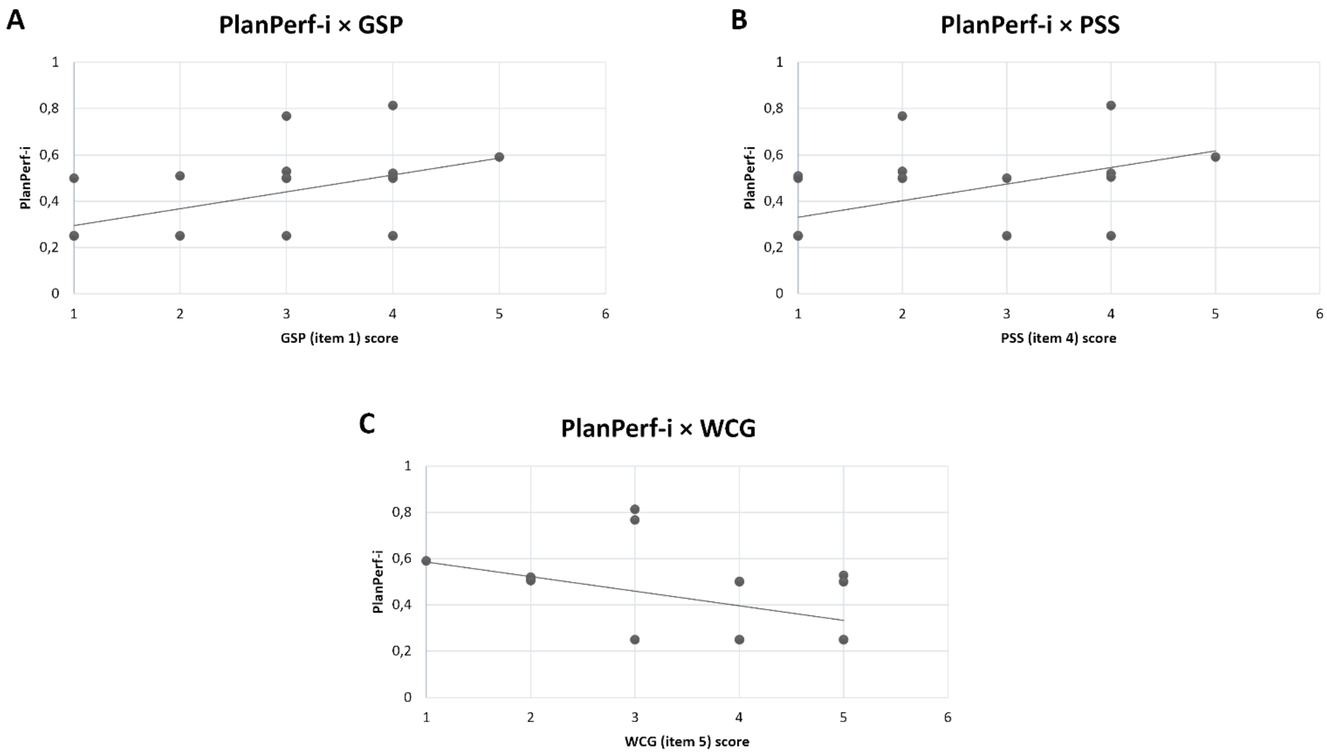

Figure 18. Pearson correlational results between the index PlanPerf-i and metacognitive measures. The scatter plots display (A) a significant positive correlation between PlanPerf-i and GSP (item 1), measuring the global use of strategic planning, (B) a significant positive correlation between PlanPerf-i and PSS (item 4), assessing participants' perception of having used a successful strategy, and (C) a negative correlation between PlanPerf-i and WCG (item 5), expressing the willingness to change strategy a posteriori.

4.3.7.2 Step two - correlations between the metacognitive measures and EEG data

Concerning the correlation between metacognitive items and EEG data a positive correlation was observed between WCG item and the power of delta in AF7 location (r =.561, p =.010) (Fig. 19). No other significant correlations were observed.

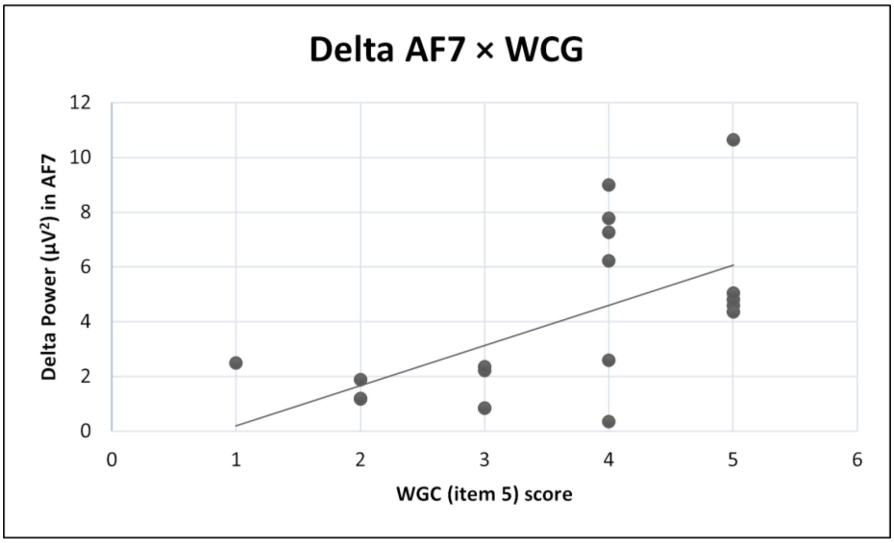

Figure 19. Pearson correlational result between metacognition measures and EEG data. The scatter plots display a positive correlation between WCG (item 5), measuring the Willingness to Change Strategy a posteriori, and the power of EEG delta band in AF7 location.

4.3.7.3 Step three - correlations between the psychometric data, metacognitive measures, and EEG data

With reference to the correlation between the significant metacognitive item and psychometric data, first, a positive correlation between the BFI Emotional Stability subscale and PSS item (r =.474, p =.035) was found (Fig. 20A).

Secondly, a negative correlation between the GDMS intuitive subscale and WCG (r = −.498, p =.025) was identified (Fig. 20B). No other significant correlations were identified between psychometric data and metacognition items.

For EEG data, a positive correlation between the BFI Conscientiousness subscale and the EEG Beta band in AF7 (r =.629, p =.007) (Fig. 20C), as well as between MS High Standards and the EEG Beta band in AF7 was found (r =.489, p =.046) (Fig. 20D). No other significant correlations were observed between this set of data.

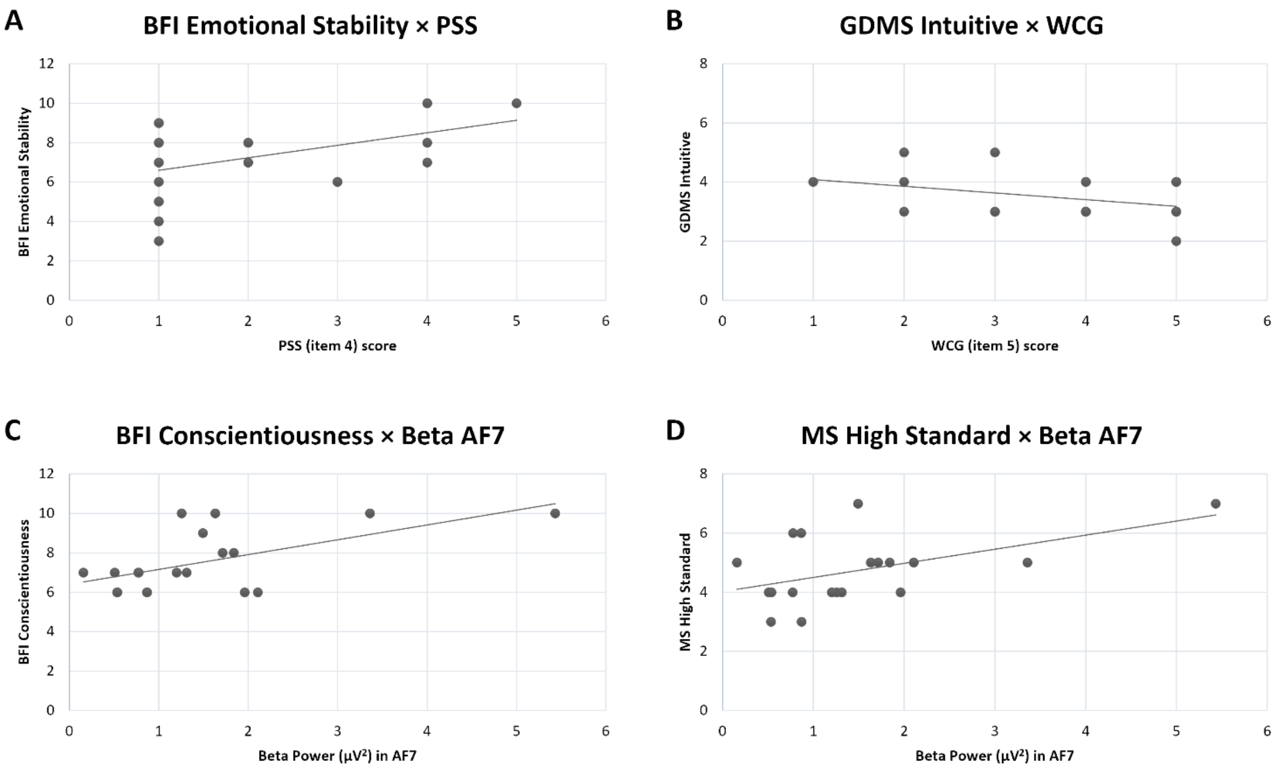

Figure 20. Pearson correlational result between psychometric data, metacognition measures and EEG data. With reference to the relation between psychometric data and metacognition items, the first two scatter plots display (A) a significant positive correlation between BFI Emotional Stability subscale and PSS (item 4), assessing participants' perception of having used a successful strategy, (B) a negative correlation between GDMS intuitive subscale and WCG (item 5), measuring the willingness to change strategy a posteriori. Also, concerning the link between psychometric data and EEG data, the last two scatter plots display a positive correlation (C) between BFI Conscientiousness subscale and EEG Beta band in AF7, and (D) between MS High Standards and EEG Beta band in AF7 electrode.

4.3.7.4 Step four - correlations between the psychometric measures

To better determine the relation between individual's personality profiles and decision-making styles, correlation analyses were performed between each BFI, GDMS, and MS subscale.

A positive correlation was observed also between the GDMS intuitive subscale and the BFI Openness subscale (r =.469, p =.024) (Fig. 6a), as well as between the GDMS intuitive subscale and the MS Alternative Search (r =.629, p =.001) (Fig. 6b). Finally, a positive correlation was found between the MS High Standards and the GDMS Rational subscale (r =.544, p =.007) (Fig. 6c). No other significant correlations were observed between the psychometric subscales.

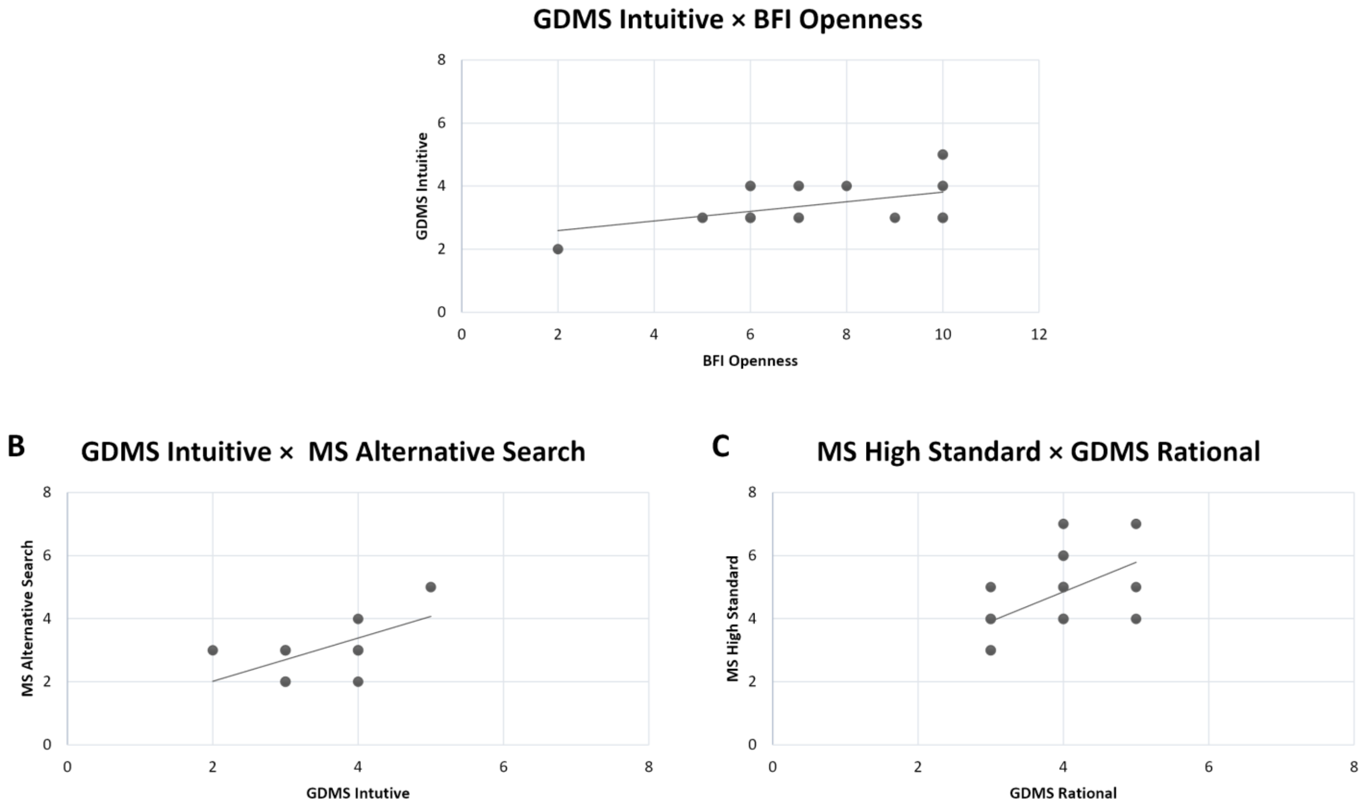

Figure 21. Pearson correlational result between psychometric scales (BFI, GDMS and MS subscales). The scatter plots display a positive correlation (A) between GDMS intuitive subscale and BFI openness subscale, (B) as well as between GDMS intuitive subscale and MS alternative search, and (C) between MS high standards and GDMS rational subscale.

4.4 Discussion

The current study explored the relationship between behavioural and EEG correlates of strategic planning abilities – assessed using a modified version of the TOH task – and the "metacognition of one's planning strategy", as well as the link between the performance and individual differences (personality profiles and decision-making styles). To achieve this purpose, a multi-level neuroscientific approach was used to collect information on (i) behavioural performance, which is determined by the levels completed in the TOH task and the corresponding RTs (computed in *Plan-Perf*-i); (ii) EEG indices, which reflect higher level mental processes, decision-making linked to performance and vigilance; (iii) metacognition, through a 5 items scale (Angioletti et al., 2020; Balconi et al., 2014, 2015). These multiple measures were correlated with psychometric scales to evaluate a possible relationship between task performance, metacognition, and individual differences in personality profiles and decision-making styles (measured through the BFI, GDMS and MS scales). Some interesting and key findings were observed which will be discussed below.

Firstly, the positive correlation found between the *PlanPerf*-i and the GSP and PSS, suggests that in our sample a better behavioral performance is predominantly connected to the global use of strategic planning and the perception of effectiveness of the strategy used during the task. This indicate that a better task performance is correlated to knowledge about cognition components rather than monitoring processes. Indeed, no significant correlations were observed between the behavioral performance and the metacognitive dimensions related to the monitoring of one's cognition, that is the awareness of being using a strategy (SA) and the change of strategy during the task (SC). So, individuals who manage to carry out a complex decision-making task efficiently seem to be those who have planned a good overall strategy and managed to perceive it as effective, rather than those who monitor performance during the task or change the strategy.

More interestingly, the more our participants were able to achieve a good performance on the task, the less they reported intending to change the strategy they used (as demonstrated by negative correlation between *PlanPerf*-i and WCG). In other words, participants that perform better were also coherently better able to consciously metacontrol their performance, through the metacognition of one's strategic planning, and decided not to change their strategy in the future in a similar decision-making task. This result is in line with a previous study which showed a significant negative correlation between the accuracy in a complex dual task and WCG: as accuracy increases, the willingness to change a strategy decreases (Balconi, Acconito, et al., 2023).

These findings are in line with what we initially hypothesized, but additionally suggest that the self-report measure we used to measure metacognition (i.e., the 5-item metacognitive scale) (Angioletti et al., 2020; Balconi et al., 2014, 2015) allows us to differentiate between the specific components and multiple levels of metacognition related to strategic planning performance. They also suggest a specific metacognitive profile for individuals who successfully perform a complex decision-making and strategic planning task.

A second interesting result concerned a specific EEG pattern activated during the task execution that is linked to the metacognition of one's strategic planning. Indeed, findings showed a positive correlation between the higher EEG delta power in in the left frontal cortex (AF7) during task execution and WCG. In the neuroscientific literature, delta band has been associated with several cognitive processing (Başar et al., 2001), including attention and the identification of salient stimuli (Knyazev, 2007; Knyazev et al., 2009) and behavioural inhibition (Kamarajan et al., 2004; Knyazev, 2007; Putman, 2011) . A positive correlation between delta waves during task completion and the ability exhibited in task execution was found. This result, according to the authors, indicates the presence of an inhibitory mechanism that would selectively inhibit neural activity considered irrelevant or inappropriate during the execution of a cognitive task: specifically, during the execution of a cognitive task that requires a certain level of attention, delta waves originating in the frontal cortex can exert a modulatory influence on neural networks located in regions far from the frontal lobes (Harmony, 2013). Interestingly, the association between cognition and the delta band might be also moderated by motivation, with cognitive performance enhanced in conditions of heightened motivation (Knyazev, 2012).

Regarding TOH task, a former work showed that delta band power increased during TOH performance in healthy adults (Guevara et al., 2013), suggesting both the involvement of concentration and focus on the task (Harmony et al., 1996) as well as decision-making processes (Başar-Eroglu et al., 1992). Moreover, this delta activation was localized in the left frontal area. Prior studies using TOH showed that a higher task complexity (i.e., a higher number of movements required to reach the target state) resulted in higher left DLPFC activity, a PFC portion previously linked to the identification of information pertinent to the goal and the development of an internal problem representation (Ruocco et al., 2014) .

Therefore, as suggested by these former works (Başar-Eroglu et al., 1992; Guevara et al., 2013; Ruocco et al., 2014), an increase in delta activity during TOH task performance over left frontal cortex (AF7) might indicate a high level of attention and concentration and inhibitory mechanisms to face this high cognitive demanding task as well as decision-making processes (due to the nature of the task itself, which requires the individual to decide which disk move next). In our study, the delta band over the left frontal cortex (AF7) was positively related with the WCG (metacognition of one's strategic planning) that has to do with the will to change the strategy a posteriori. Starting from the functional meaning of delta power increase in the left DLPFC (Başar-Eroglu et al., 1992; Guevara et al., 2013; Ruocco et al., 2014), it could be speculated that the increase in delta activity over the left frontal cortex (AF7) during the TOH task indicates a greater cognitive effort, likely due to the challenging nature of the task, which is strictly related to the participant intention to change the strategy in the future (either to achieve better results or to reduce the effort required).

Another possible interpretation of this result could be that individuals who show a reduction in the delta band power in the left frontal cortex (AF7) during the TOH task – perhaps because they find it simpler and more feasible with less need for attention, concentration, inhibitory and decision-making mechanisms during the task – are those who decided not to change their strategy in the future in a similar decision-making task. This second explanation could be in line with the correlational result between the *PlanPerf*-i and WCG, so that as successful behavioral performance increases, there is a decrease in the willingness to change a strategy. And, in turn, this decrease in willingness to change a strategy is also accompanied by a reduction in the delta band power in the left frontal cortex (AF7).

However, no previous research explored the relation between the EEG markers of the TOH and the WCG. In a previous study using the same metacognition assessment tool, administered after the execution of a complex dual task (during which the EEG data was collected), no significant results were found in relation to the EEG delta band and the WCG (Balconi, Acconito, et al., 2023). Therefore, these interpretations should be considered with caution because future studies are needed to corroborate this finding and more directly link this specific EEG delta pattern, the outcome to behavioral performance and the metacognition of one's strategic planning.

Thirdly, this study adds to the existing literature some novel results regarding the relation between the EEG pattern supporting TOH task performance, the metacognitive results, and specific individual differences (here considered in terms of personality profiles and decision-making styles).

Starting from the relation between individual differences and EEG correlates, it was found a positive correlation between the power of EEG beta band over the left frontal cortex (AF7) and BFI Conscientiousness subscale, as well as with MS High Standards subscale. In addition, in the considered sample, higher MS High Standards subscale scores were also associated with higher GDMS Rational subscale scores. Taken together, this outcome suggests that in individuals who are orderly, responsible, and dependable, who tend to hold high standards for themselves and things in general, as well as make decisions based on careful consideration and evaluation of different alternatives, an increase of EEG beta power over the left frontal regions during the TOH task. This result is only partially in line with our hypotheses since we expected to observe a variation in EEG delta rather than beta power, according to the existing literature (Guevara et al., 2013; Ruocco et al., 2014). Still, it is plausible that for individuals with the previously described specific personality profiles, the execution of TOH task is characterized by a different EEG pattern in the left frontal cortex (AF7) suggesting higher mental effort both in terms of emotional and cognitive processes, according to the functional meaning of EEG beta band (Ray & Cole, 1985b). Recent neuroscientific studies have associated the increased power of beta band in the frontal areas with learning and the processing of positive feedback (Luft, 2014; Marco-Pallarés et al., 2015), two cognitive and emotional processes that intervene during the execution of TOH task, and that were shown to be related to the previously mentioned individual's profile in this study. Future studies are needed to distinguish more directly the role of beta and delta bands during decision-making and strategic planning activities. However, it seems that for some personality profiles the power of the beta band supports task performance, while the delta band varies in association with the metacognition of one's strategic planning, regardless the personality profile.

Regarding metacognition measures and individual differences, we found that in individuals with high emotional stability, who tend to be calm, reliable, confident, express minimal dissatisfaction regarding their personal problems, and seems able to better cope with stressful situations (Hills & Argyle, 2001), there is also a higher perception of having used a successful strategy (PSS) during the task. Additionally, individuals with an intuitive decision-making style, who are more prone to make their decision almost "gut-driven" and based on their first intuition, rely mostly on their "feeling" and first impression, but also are open to new experiences and tend to seek better decisional options (given the positive correlation with to BFI Openness and MS Alternative Search subscale scores), are less likely to change their decision and strategy in the future in a similar decision-making task. These outcomes related to individual differences promote reflection on how individuals with different personality profiles and decision-making styles approach a strategic planning dynamic when faced with a complex decision and implement different levels of metacognition. Such evidence can be of interest even in applied contexts, like in professional context, where the human resources recruitment process could be focus on the selection of candidates with specific characteristics, who know how to successfully deal with complex decision-making and exploit the metacognition of one's strategic planning.

To conclude, the findings of the current study highlighted the value of exploiting a multi-level neuroscientific approach when exploring the metacognition of one's strategic planning in decision-making. The construct of metacognition has proven to be the cornerstone that intertwines relationships both with behavioral performance, with EEG data that support decision-making performance and with individual differences. Furthermore, current results allow researchers to delve deeper into the multiple levels of metacognition, pointing out the significance of metacognition of one's strategic planning.

Although there are some strengths and innovations in this work, it is not exempt from shortcomings. First, the experimental sample size should be expanded in the future to increase the generalizability of the results. Moreover, the neuroscientific literature on the correlates of metacognitive components and levels is relatively scarce to date. Hence, the current evidence has been interpreted considering the available scientific literature and must be treated with caution. Also, in this study, only one way of measuring metacognition was used (i.e., the self-report metacognitive scale), while in the future we could also include a self-report questionnaire, such as the MAI (Gregory & Sperling, 1994) or the MSLQ (Pintrich et al., 1993), or a post-decision wagering procedure focused on the behavioral performance of the person to better explore the construct of metacognition from multiple perspectives. Furthermore, in this work, a wearable EEG device with a small number of derivations (four electrodes located on frontal and temporoparietal regions) was used, and information from only these available locations was collected. To explore metacognition from a multi-methodological point of view it would prove necessary and interesting to develop basic neuroscience research that allows a more extensive EEG data collection on the scalp and to identify the EEG correlates of the different dimensions of metacognition. In addition, the correlations between EEG as a continuous variable and Likert scales that are fixed to a range of scores and limited to a short number of items could be considered a limitation of this study. This limitation is not unique to the present study; it affects all studies using a mixed method approach. Although this mixed method approach adds value by reporting the correlation between Likert scales and EEG data and by comparing different levels of investigation that are otherwise difficult to understand, it presents also this limitation inherent in the metric itself.

Moreover, the relationship between individual differences (personality profiles and decision-making style) and behavioral performance has been explored in some studies with decision-making tasks (Buelow & Cayton, 2020), but not with the TOH task specifically. Similarly, few studies have explored the relationship between individual differences and metacognitive components (Basu & Dixit, 2022; Colombo et al., 2010). Therefore, in order to assess the robustness of the current correlational findings, it would be beneficial to replicate them in subsequent research.

Chapter 5 – General discussion and conclusion

This doctoral dissertation aimed to contribute to the theoretical and empirical understanding of decision-making by approaching it as a dynamic and multilayered process, in which cognitive, affective, and metacognitive components interact in complex and context-dependent ways. Starting from an excursus on EFs theories and contemporary neuroscientific models, the project sought to explore how feedback – whether positive or negative – modulates decision-making, particularly in relation to memory recall, behavioral adaptation, and strategic self-regulation, and to explore the role of metacognitive awareness, particularly focusing on individuals' ability to monitor, evaluate, and regulate their own decision strategies during the execution of complex tasks.

As discussed in the earlier sections of the introduction, decision-making has emerged in cognitive neuroscience as one of the most ecologically relevant and intricate expressions of executive functioning, involving the integration of cognitive control, emotional regulation, and metacognitive monitoring (Miller & Cohen, 2001). Far from representing a purely rational or isolated process, decision-making is increasingly conceptualized as a dynamic interaction between "cold" cognitive operations (such as working memory and inhibition) and "hot" affective and motivational systems (Diamond, 2013; Zelazo & Carlson, 2012), both of which are deeply influenced by contextual factors such as feedback valence and perceived uncertainty.

Despite the theoretical recognition of this complexity, many empirical studies have treated these components in isolation, limiting our understanding of how they function in real-world settings. In particular, little is known about how the emotional tone of feedback (i.e., its valence) affects the encoding and retrieval of decision-related memories in healthy populations, especially when examined through neurophysiological markers in ecologically valid contexts. Additionally, while the role of metacognition in decision-making is widely acknowledged (Flavell, 1979; Fleming, 2023) few studies have explored second-order metacognitive abilities, that is, the capacity to reflect on and adapt one's own strategies during complex decisional tasks.

Accordingly, this project investigated three core dimensions: (1) the valence of feedback as a modulating factor in decision memory; (2) the persistence of cognitive biases, such as the status quo bias, in situations of feedback mismatch or uncertainty; and (3) the role of metacognition in guiding strategic planning and behavioral flexibility. Through the integration of behavioral data and EEG measures – collected in ecologically valid tasks and supported by wearable technologies – this research aimed to overcome the limitations of purely behavioral paradigms and to capture the unfolding of decision-related processes in more naturalistic conditions.

In light of these premises, the present chapter offers a critical interpretation of the empirical findings, aligning them with the theoretical constructs outlined earlier in the thesis. It discusses their implications from theoretical, methodological, and applied perspectives, and sets the stage for identifying future research directions within the broader framework of cognitive neuroscience and decision science.

Specifically, the first study investigated the impact of positive and negative feedback on the recall of past decisions, examining both behavioral performance and EEG responses. At the behavioral level, accurately recalled decisions associated with positive feedback showed slower RTs compared to those linked to negative feedback. This suggests a potential attentional bias toward positive information, which may increase cognitive load during memory retrieval.

EEG data revealed distinct patterns: a general reduction in alpha band activity over frontal areas (AF7, AF8) was observed for both correct and incorrect recalls, indicating focused attention and cognitive control. Notably, erroneously recalled decisions associated with negative feedback showed lower alpha power in AF7 compared to TP10, suggesting insufficient temporo-parietal processing to support accurate recall under self-threatening feedback conditions. Correctly recalled decisions following negative feedback exhibited increased delta band activity, commonly associated with aversive states. In contrast, erroneously recalled decisions with negative feedback displayed higher beta and gamma activity, indicating greater cognitive effort required to process negative memories, or possibly reflecting an attempt at selective forgetting (mnemic neglect effect) of feedback perceived as threatening to the self.

Taken together, these results suggest that recalling decisions associated with self-threatening feedback requires greater cognitive effort, and that the alignment between feedback content and an individual's existing self-concept may influence behavioral and neural responses more strongly than the mere valence of the feedback itself.

The second study investigated decision-makers' sensitivity to external signals, such as positive and negative reinforcement, their flexibility in using feedback to modify or maintain their choices, as well as the associated neurofunctional correlates and decision-making styles. The main findings revealed a marked tendency among participants to stick with their initial decisions, an expression of status quo bias, both after receiving positive reinforcement and in the absence of explicit feedback. Surprisingly, some participants even maintained their decisions after receiving negative feedback, suggesting that this bias may be strong enough to hinder behavioral correction.

At the neurofunctional level, lower cognitive effort – reflected in reduced prefrontal beta power – was observed following positive feedback, indicating that fewer mental resources are required when decisions are externally validated. Moreover, negative correlations were found between the "dependent" decision-making style (as measured by the GDMS) and task performance in both the positive feedback and no-feedback conditions, while a positive correlation emerged between the "spontaneous" decision-making style and performance in the no-feedback condition.

These findings have important implications for understanding both adaptive and maladaptive decision-making processes and may inform strategies aimed at reducing cognitive inertia and promoting flexible, feedback-sensitive behavior.

Finally, the third study examined metacognition of one's own planning strategy in relation to behavioral and EEG correlates during a complex decision-making task, also exploring the link with individual differences such as personality profiles and decision-making styles. The results showed that the metacognitive scale used can differentiate specific dimensions and levels of metacognition related to performance and decision-making in strategic planning. A positive correlation was found between EEG delta power over the left frontal cortex (AF7) during the task and metacognition of one's planning strategy across the entire sample. Additionally, increased beta activity over the left frontal cortex (AF7) during task execution, along with higher metacognitive beliefs of efficacy and lower willingness to change the strategy afterwards, were found to be correlated with specific personality profiles and decision-making styles. These findings allow researchers to deepen the understanding of the multiple facets of metacognition of one's planning strategy in the decision-making process.

5.1 Practical implications and future perspectives

Building on the findings of this thesis and looking ahead to future developments, it would be valuable to highlight various practical implications across multiple fields, such as management, clinical practice, and empowerment.

Findings from Balconi, Allegretta, et al. (2025) highlight the predictive role of second-level metacognition – defined as the awareness and regulation of one's planning strategy – in complex decision-making tasks such as the Tower of Hanoi. This suggests the practical utility of simplified yet effective metacognitive assessment tools in educational, clinical, and organizational settings. For instance, short metacognitive scales could be used to monitor and strengthen individuals' strategic awareness, thereby improving self-efficacy and the ability to learn from errors and feedback in both academic and professional training environments.

Balconi, Angioletti, et al. (2025) demonstrate that feedback valence (positive or negative) significantly influences not only decision recall accuracy but also the cognitive and emotional processing associated with it, as reflected in EEG band activity (e.g., increased delta for negative feedback, gamma for incorrect responses). These findings open the door to feedback-informed adaptive learning systems, where feedback is tailored in real-time to enhance encoding and retrieval processes, potentially integrated into intelligent tutoring systems or e-learning platforms that account for the learner's cognitive load and emotional state.

The study by Crivelli et al. (2023) reveals that, despite the presence of negative feedback, individuals often maintain their previous choices, reflecting a status quo bias. This insight is highly relevant for applied contexts where behavioral rigidity can be detrimental, such as leadership training, risk management, or strategic planning. Wearable EEG technologies and neurofeeddback may provide real-time indicators of cognitive flexibility and feedback sensitivity, allowing for targeted interventions to enhance adaptive decision-making in organizational and high-stakes environments.

Overall, based on the results obtained, the future directions of this work point toward identifying practical implications across various applied contexts, including management, clinical, and educational domains. In particular, the exploration of metacognitive processes and their influence on complex decision-making opens the way for the development of tools aimed at assessing and enhancing individuals' strategic skills, including brief and easy-to-administer scales. These tools could be integrated into training, rehabilitation, or professional development programs, with the goal of improving self-efficacy, the ability to learn from feedback, and adaptability to change. Similarly, the analysis of the role of feedback and its cognitive and emotional components suggests the opportunity to design adaptive learning and decision-support systems capable of modulating information based on an individual's cognitive and emotional state. Lastly, the identification of factors such as behavioral rigidity or the tendency to maintain the status quo highlights the importance of fostering cognitive flexibility in highly complex environments, through innovative neurophysiological monitoring technologies and targeted interventions aimed at supporting more effective and adaptive decision-making processes.

From a clinical perspective, the findings suggest several potential directions for applied development. In particular, the assessment of metacognition and decision-making dynamics could serve as a valuable indicator for diagnosing and monitoring neuropsychological or psychopathological conditions in which strategic awareness, cognitive flexibility, or the ability to learn from errors are impaired. The use of brief and standardized tools to detect these processes would enable timely and personalized interventions, even in settings with limited resources. Moreover, the integration of non-invasive neurophysiological technologies – such as wearable EEG devices – could support real-time monitoring of patients' cognitive and emotional states, offering new avenues for biofeedback, cognitive rehabilitation, and emotional regulation. Finally, a deeper understanding of the mechanisms underlying feedback response and the persistence of dysfunctional behaviors may contribute to the development of clinical protocols aimed at improving treatment adherence, error management, and adaptability to change, with a direct impact on quality of life and the overall therapeutic process.

5.2 Limitations

Although the three studies offer valuable insights into decision-making, metacognition, feedback and emotional-cognitive regulation, several limitations should be acknowledged to contextualize their findings and inform future research. First, all studies are based on relatively small and homogeneous samples, typically composed of healthy adults with similar educational backgrounds and no history of neurological or psychiatric conditions, limiting the generalizability of the results to broader populations.

A shared methodological choice across studies is the use of wearable EEG devices, which, while offering advantages in terms of ecological validity, cost-effectiveness, and portability, also present notable technical limitations. Specifically, the reduced spatial resolution of wearable EEG systems – compared to high-density lab-based EEG – restricts the accuracy in localizing neural generators, especially for deeper cortical or subcortical structures. The limited number of electrodes (often restricted to prefrontal and temporoparietal sites, such as AF7, AF8, TP9, and TP10) provides only a partial view of the overall neural dynamics involved in complex decision-making and metacognitive monitoring. Additionally, these systems are more susceptible to motion artifacts and environmental noise, requiring careful data cleaning procedures that may still not eliminate all sources of contamination.

Another limitation lies in the lack of neutral or control conditions in some protocols (e.g., absence of a no-feedback condition in the first study), which hinders the isolation of specific effects related to feedback valence or cognitive strategy. Furthermore, several findings rely on post-task self-report questionnaires, which, while useful, are inherently limited by subjective biases such as social desirability and variable metacognitive insight. Finally, although individual differences in personality traits and decision-making styles are considered, these aspects are only exploratorily addressed and not always integrated as primary factors in the analyses, highlighting the need for more systematic, large-scale investigations to assess their modulatory roles.

Altogether, these limitations point toward the importance of adopting more robust experimental designs, incorporating multimodal neuroimaging approaches, and extending the research to clinical or diverse populations. Such advances will be essential to validate the current findings and support their translational application in real-world decision-making contexts.

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References

Abendroth, J., Nauroth, P., Richter, T., & Gollwitzer, M. (2022). Non-strategic detection of identity-threatening information: Epistemic validation and identity defense may share a common cognitive basis. *PLoS ONE*, *17*(1), e0261535. https://doi.org/10.1371/journal.pone.0261535

Acabchuk, R. L., Simon, M. A., Low, S., Brisson, J. M., & Johnson, B. T. (2021). Measuring Meditation Progress with a Consumer-Grade EEG Device: Caution from a Randomized Controlled Trial. *Mindfulness*, *12*(1), 68–81. https://doi.org/10.1007/s12671-020-01497-1

Albrecht, C., Vijver, R. van de, & Bellebaum, C. (2023). Learning new words via feedback—Association between feedback-locked ERPs and recall performance—An exploratory study. *Psychophysiology*, *60*(10), e14324. https://doi.org/10.1111/psyp.14324

Allegretta, R. A., Rovelli, K., & Balconi, M. (2024). The Role of Emotion Regulation and Awareness in Psychosocial Stress: An EEG-Psychometric Correlational Study. *Healthcare*, *12*(15), 1491. https://doi.org/10.3390/healthcare12151491

Anderson, C. J. (2003). The Psychology of Doing Nothing: Forms of Decision Avoidance Result From Reason and Emotion. *Psychological Bulletin*, *129*(1), 139–167. https://doi.org/10.1037/0033-2909.129.1.139

Anderson, M. C., & Green, C. (2001). Suppressing unwanted memories by executive control. *Nature*, *410*(6826), 366–369. https://doi.org/10.1038/35066572

Angioletti, L., Campanella, S., & Balconi, M. (2020). Metacognition deficits and impulsivity in Parkinson's Disease patients with and without gambling behavior: A pilot study. *Neurology, Psychiatry and Brain Research*, *36*, 88–95. https://doi.org/10.1016/j.npbr.2020.04.002

Ardila, A. (2008). On the evolutionary origins of executive functions. *Brain and Cognition*, *68*(1), 92–99. https://doi.org/10.1016/j.bandc.2008.03.003

Aron, A. R., Shohamy, D., Clark, J., Myers, C., Gluck, M. A., & Poldrack, R. A. (2004). Human Midbrain Sensitivity to Cognitive Feedback and Uncertainty During Classification Learning. *Journal of Neurophysiology*, *92*(2), 1144–1152. https://doi.org/10.1152/jn.01209.2003

Baddeley, A. (1996). The fractionation of working memory. *Proceedings of the National Academy of Sciences*, *93*(24), 13468–13472. https://doi.org/10.1073/pnas.93.24.13468

Baddeley, A., Eysenck, M. W., & Anderson, M. C. (2020). *Memory* (3rd ed.). Routledge. https://doi.org/10.4324/9780429449642

Baddeley, A., & Hitch, G. (1974). Working Memory. *Psychology of Learning and Motivation*, *8*, 47–89. https://doi.org/10.1016/s0079-7421(08)60452-1

Baggetta, P., & Alexander, P. A. (2016). Conceptualization and Operationalization of Executive Function. *Mind, Brain, and Education*, *10*(1), 10–33. https://doi.org/10.1111/mbe.12100

Balconi, M. (2023). Why a dynamic multicomponential model of decision making: some milestones and a preliminary tool. *Neuropsychological Trends*, *33*, 9–16. https://doi.org/10.7358/neur-2023-033-balm

Balconi, M., Acconito, C., Allegretta, R. A., & Angioletti, L. (2024). Neurophysiological and Autonomic Correlates of Metacognitive Control of and Resistance to Distractors in Ecological Setting: A Pilot Study. *Sensors*, *24*(7), 2171. https://doi.org/10.3390/s24072171

Balconi, M., Acconito, C., Allegretta, R. A., & Crivelli, D. (2023). What Is the Relationship between Metacognition and Mental Effort in Executive Functions? The Contribution of Neurophysiology. *Behavioral Sciences*, *13*(11), 918. https://doi.org/10.3390/bs13110918

Balconi, M., Allegretta, R. A., & Angioletti, L. (2023). Autonomic synchrony induced by hyperscanning interoception during interpersonal synchronization tasks. *Frontiers in Human Neuroscience*, *17*, 1200750. https://doi.org/10.3389/fnhum.2023.1200750

Balconi, M., Allegretta, R. A., & Angioletti, L. (2025). Metacognition of one's strategic planning in decision-making: the contribution of EEG correlates and individual differences. *Cognitive Neurodynamics*, *19*(1), 4. https://doi.org/10.1007/s11571-024-10189-8

Balconi, M., Angioletti, L., & Acconito, C. (2023). Self-Awareness of Goals Task (SAGT) and Planning Skills: The Neuroscience of Decision Making. *Brain Sciences*, *13*(8), 1163. https://doi.org/10.3390/brainsci13081163

Balconi, M., Angioletti, L., & Allegretta, R. A. (2025). Which type of feedback—Positive or negative- reinforces decision recall? An EEG study. *Frontiers in Systems Neuroscience*, *18*, 1524475. https://doi.org/10.3389/fnsys.2024.1524475

Balconi, M., Angioletti, L., & Crivelli, D. (2020). Neuro-Empowerment of Executive Functions in the Workplace: The Reason Why. *Frontiers in Psychology*, *11*, 1519. https://doi.org/10.3389/fpsyg.2020.01519

Balconi, M., Angioletti, L., & Rovelli, K. (2024). Neurophysiological response to social feedback in stressful situations. *European Journal of Neuroscience*, *60*(8), 6030–6045. https://doi.org/10.1111/ejn.16528

Balconi, M., Brambilla, E., & Falbo, L. (2009). BIS/BAS, cortical oscillations and coherence in response to emotional cues. *Brain Research Bulletin*, *80*(3), 151–157. https://doi.org/10.1016/j.brainresbull.2009.07.001

Balconi, M., & Campanella, S. (2021). *Advances in Substance and Behavioral Addiction:* (M. Balconi & S. Campanella, Eds.). Springer Cham. https://doi.org/10.1007/978-3-030-82408-2

Balconi, M., & Crivelli, D. (2010). Veridical and false feedback sensitivity and punishment-reward system (BIS/BAS): ERP amplitude and theta frequency band analysis. *Clinical Neurophysiology*, *121*(9), 1502–1510. https://doi.org/10.1016/j.clinph.2010.03.015

Balconi, M., & Crivelli, D. (2021). The Assessment of Executive Functions: A New Neuropsychological Tool for Addiction. In M. Balconi & S. Campanella (Eds.), *Advances in Substance and Behavioral Addiction* (pp. 61–85). Springer. https://doi.org/10.1007/978-3-030-82408-2_3

Balconi, M., Crivelli, D., Castiglioni, C., & Lozza, E. (2019). Social frame and tax compliance modulate electrophysiological and autonomic responses following tax-related decisions. *Scientific Reports*, *9*(1), 4713. https://doi.org/10.1038/s41598-019-41156-7

Balconi, M., Finocchiaro, R., & Campanella, S. (2014). Reward Sensitivity, Decisional Bias, and Metacognitive Deficits in Cocaine Drug Addiction. *Journal of Addiction Medicine*, *8*(6), 399–406. https://doi.org/10.1097/adm.0000000000000065

Balconi, M., Finocchiaro, R., & Canavesio, Y. (2015). Reward Sensitivity (Behavioral Activation System), Cognitive, and Metacognitive Control in Gambling Behavior: Evidences From Behavioral, Feedback-Related Negativity, and P300 Effect. *The Journal of Neuropsychiatry and Clinical Neurosciences*, *27*(3), 219–227. https://doi.org/10.1176/appi.neuropsych.14070165

Balconi, M., Losasso, D., Balena, A., & Crivelli, D. (2022). Neurocognitive impairment in addiction: A digital tool for executive function assessment. *Frontiers in Psychiatry*, *13*, 955277. https://doi.org/10.3389/fpsyt.2022.955277

Balconi, M., Rovelli, K., Angioletti, L., & Allegretta, R. A. (2024). Working Memory Workload When Making Complex Decisions: A Behavioral and EEG Study. *Sensors*, *24*(17), 5754. https://doi.org/10.3390/s24175754

Başar, E., Başar-Eroglu, C., Karakaş, S., & Schürmann, M. (2001). Gamma, alpha, delta, and theta oscillations govern cognitive processes. *International Journal of Psychophysiology*, *39*(2–3), 241–248. https://doi.org/10.1016/s0167-8760(00)00145-8

Başar-Eroglu, C., Başar, E., Demiralp, T., & Schürmann, M. (1992). P300-response: possible psychophysiological correlates in delta and theta frequency channels. A review. *International Journal of Psychophysiology*, *13*(2), 161–179. https://doi.org/10.1016/0167-8760(92)90055-g

Bastos, A. M., Vezoli, J., Bosman, C. A., Schoffelen, J.-M., Oostenveld, R., Dowdall, J. R., De Weerd, P., Kennedy, H., & Fries, P. (2015). Visual Areas Exert Feedforward and Feedback Influences through Distinct Frequency Channels. *Neuron*, *85*(2), 390–401. https://doi.org/10.1016/j.neuron.2014.12.018

Basu, S., & Dixit, S. (2022). Role of metacognition in explaining decision-making styles: A study of knowledge about cognition and regulation of cognition. *Personality and Individual Differences*, *185*, 111318. https://doi.org/10.1016/j.paid.2021.111318

Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010

Berns, G. S., McClure, S. M., Pagnoni, G., & Montague, P. R. (2001). Predictability Modulates Human Brain Response to Reward. *The Journal of Neuroscience*, *21*(8), 2793–2798. https://doi.org/10.1523/jneurosci.21-08-02793.2001

Biasiucci, A., Franceschiello, B., & Murray, M. M. (2019). Electroencephalography. *Current Biology*, *29*(3), R80–R85. https://doi.org/10.1016/j.cub.2018.11.052

Bleichner, M. G., & Debener, S. (2017). Concealed, Unobtrusive Ear-Centered EEG Acquisition: cEEGrids for Transparent EEG. *Frontiers in Human Neuroscience*, *11*, 163. https://doi.org/10.3389/fnhum.2017.00163

Botvinick, M. M., Cohen, J. D., & Carter, C. S. (2004). Conflict monitoring and anterior cingulate cortex: an update. *Trends in Cognitive Sciences*, *8*(12), 539–546. https://doi.org/10.1016/j.tics.2004.10.003

Boyd, R. (2006). The Puzzle of Human Sociality. *Science*, *314*(5805), 1555–1556. https://doi.org/10.1126/science.1136841

Boyer, M., & Robert, J. (2006). Organizational inertia and dynamic incentives. *Journal of Economic Behavior & Organization*, *59*(3), 324–348. https://doi.org/10.1016/j.jebo.2004.06.024

Brand, M., Labudda, K., & Markowitsch, H. J. (2006). Neuropsychological correlates of decision-making in ambiguous and risky situations. *Neural Networks*, *19*(8), 1266–1276. https://doi.org/10.1016/j.neunet.2006.03.001

Braver, T. S. (2012). The variable nature of cognitive control: a dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Breiter, H. C., Aharon, I., Kahneman, D., Dale, A., & Shizgal, P. (2001). Functional Imaging of Neural Responses to Expectancy and Experience of Monetary Gains and Losses. *Neuron*, *30*(2), 619–639. https://doi.org/10.1016/s0896-6273(01)00303-8

Brevers, D., Cleeremans, A., Bechara, A., Greisen, M., Kornreich, C., Verbanck, P., & Noël, X. (2013). Impaired Self-Awareness in Pathological Gamblers. *Journal of Gambling Studies*, *29*(1), 119–129. https://doi.org/10.1007/s10899-012-9292-2

Brodmann, K. (1909). *Vergleichende Lokalisationslehre der Großhirnrinde in ihren Prinzipien dargestellt auf Grund des Zellenbaues*. Barth.

Buelow, M. T., & Cayton, C. (2020). Relationships between the big five personality characteristics and performance on behavioral decision making tasks. *Personality and Individual Differences*, *160*, 109931. https://doi.org/10.1016/j.paid.2020.109931

Bull, R., Espy, K. A., & Senn, T. E. (2004). A comparison of performance on the Towers of London and Hanoi in young children. *Journal of Child Psychology and Psychiatry*, *45*(4), 743–754. https://doi.org/10.1111/j.1469-7610.2004.00268.x

Burgess, P. W., Veitch, E., Costello, A. de L., & Shallice, T. (2000). The cognitive and neuroanatomical correlates of multitasking. *Neuropsychologia*, *38*(6), 848–863. https://doi.org/10.1016/s0028-3932(99)00134-7

Burmeister, K., & Schade, C. (2007). Are entrepreneurs' decisions more biased? An experimental investigation of the susceptibility to status quo bias. *Journal of Business Venturing*, *22*(3), 340–362. https://doi.org/10.1016/j.jbusvent.2006.04.002

Butler, D. L., & Winne, P. H. (1995). Feedback and Self-Regulated Learning: A Theoretical Synthesis. *Review of Educational Research*, *65*(3), 245–281. https://doi.org/10.3102/00346543065003245

Cannard, C., Wahbeh, H., & Delorme, A. (2012). Validating the wearable MUSE headset for EEG spectral analysis and Frontal Alpha Asymmetry. *Proceedings of the IEEE International*

Conference on Bioinformatics and Biomedicine (BIBM), 3603–3610. https://doi.org/10.1109/bibm52615.2021.9669778

Carter, R. M., & Huettel, S. A. (2013). A nexus model of the temporal–parietal junction. *Trends in Cognitive Sciences*, *17*(7), 328–336. https://doi.org/10.1016/j.tics.2013.05.007

Catani, M. (2019). The anatomy of the human frontal lobe. In *Handbook of clinical neurology* (pp. 95–122). https://doi.org/10.1016/b978-0-12-804281-6.00006-9

Cavada, C., Compañy, T., Tejedor, J., Cruz-Rizzolo, R. J., & Reinoso-Suárez, F. (2000). The Anatomical Connections of the Macaque Monkey Orbitofrontal Cortex. A Review. *Cerebral Cortex*, *10*(3), 220–242. https://doi.org/10.1093/cercor/10.3.220

Cavanagh, J. F., Cohen, M. X., & Allen, J. J. B. (2009). Prelude to and Resolution of an Error: EEG Phase Synchrony Reveals Cognitive Control Dynamics during Action Monitoring. *The Journal of Neuroscience*, *29*(1), 98–105. https://doi.org/10.1523/jneurosci.4137-08.2009

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in Cognitive Sciences*, *18*(8), 414–421. https://doi.org/10.1016/j.tics.2014.04.012

Chan, R. C. K., Shum, D., Toulopoulou, T., & Chen, E. Y. H. (2008). Assessment of executive functions: Review of instruments and identification of critical issues. *Archives of Clinical Neuropsychology*, *23*(2), 201–216. https://doi.org/10.1016/j.acn.2007.08.010

Chatrian, G. E., Lettich, E., & Nelson, P. L. (1985). Ten Percent Electrode System for Topographic Studies of Spontaneous and Evoked EEG Activities. *American Journal of EEG Technology*, *25*(2), 83–92. https://doi.org/10.1080/00029238.1985.11080163

Chernev, A. (2004). Goal Orientation and Consumer Preference for the Status Quo. *Journal of Consumer Research*, *31*(3), 557–565. https://doi.org/10.1086/425090

Chick, C. F., Pardo, S. T., Reyna, V. F., & Goldman, D. A. (2017). Decision Making (Individuals). In *Encyclopedia of Human Behavior (Second Edition)*. https://doi.org/10.1016/b978-0-12-375000-6.00122-1

Chudasama, Y., & Robbins, T. W. (2006). Functions of frontostriatal systems in cognition: Comparative neuropsychopharmacological studies in rats, monkeys and humans. *Biological Psychology*, *73*(1), 19–38. https://doi.org/10.1016/j.biopsycho.2006.01.005

Chung, H. J., Weyandt, L. L., & Swentosky, A. (2014). The Physiology of Executive Functioning. In S. Goldstein & J. Naglieri (Eds.), *Handbook of Executive Functioning* (pp. 13–27). Springer. https://doi.org/10.1007/978-1-4614-8106-5_2

Cleeremans, A., Timmermans, B., & Pasquali, A. (2007). Consciousness and metarepresentation: A computational sketch. *Neural Networks*, *20*(9), 1032–1039. https://doi.org/10.1016/j.neunet.2007.09.011

Cohen, M. X., Elger, C. E., & Ranganath, C. (2007). Reward expectation modulates feedback-related negativity and EEG spectra. *NeuroImage*, *35*(2), 968–978. https://doi.org/10.1016/j.neuroimage.2006.11.056

Collette, F., Linden, M. V. der, Laureys, S., Delfiore, G., Degueldre, C., Luxen, A., & Salmon, E. (2005). Exploring the unity and diversity of the neural substrates of executive functioning. *Human Brain Mapping*, *25*(4), 409–423. https://doi.org/10.1002/hbm.20118

Colombo, B., Iannello, P., & Antonietti, A. (2010). Metacognitive Knowledge of Decision-Making: An Explorative Study. In A. Efklides & P. Misailidi (Eds.), *Trends and Prospects in Metacognition Research* (pp. 445–472). Springer. https://doi.org/10.1007/978-1-4419-6546-2_20

Conway, M. A. (2005). Memory and the self. *Journal of Memory and Language*, *53*(4), 594–628. https://doi.org/10.1016/j.jml.2005.08.005

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*(3), 201–215. https://doi.org/10.1038/nrn755

Crescentini, C., Seyed-Allaei, S., Vallesi, A., & Shallice, T. (2012). Two networks involved in producing and realizing plans. *Neuropsychologia*, *50*(7), 1521–1535. https://doi.org/10.1016/j.neuropsychologia.2012.03.005

Crespo-García, M., Wang, Y., Jiang, M., Anderson, M. C., & Lei, X. (2022). Anterior Cingulate Cortex Signals the Need to Control Intrusive Thoughts during Motivated Forgetting. *The Journal of Neuroscience*, *42*(21), 4342–4359. https://doi.org/10.1523/jneurosci.1711-21.2022

Crivelli, D. (2023). Assessing decision-making skills: preliminary proof-of-concept data for DAssDec - Mod1STY and Mod2STR. *Neuropsychological Trends*, *33*, 67–81. https://doi.org/10.7358/neur-2023-033-criv

Crivelli, D., Allegretta, R. A., & Balconi, M. (2023). The "status quo bias" in Response to External Feedback in Decision-Makers. *Adaptive Human Behavior and Physiology*, *9*(4), 426–441. https://doi.org/10.1007/s40750-023-00230-1

Crivelli, D., Allegretta, R. A., & Balconi, M. (2024). Physiology of Risk-Taking and Risk Management in Realistic Decision-Making Scenarios. *Psychological Reports*, *0*(0), 1–19. https://doi.org/10.1177/00332941241258919

Crivelli, D., & Balconi, M. (2023). Shared emotions, interpersonal syntonization, and group decision-making: a multi-agent perspective. *Frontiers in Neuroscience*, *17*, 1251855. https://doi.org/10.3389/fnins.2023.1251855

Crivelli, D., Balena, A., Losasso, D., & Balconi, M. (2024). Screening Executive Functions in Substance-Use Disorder: First Evidence from Testing of the Battery for Executive Functions in Addiction (BFE-A). *International Journal of Mental Health and Addiction*, *22*(3), 1315–1332. https://doi.org/10.1007/s11469-022-00928-5

Cunillera, T., Fuentemilla, L., Periañez, J., Marco-Pallarès, J., Krämer, U. M., Càmara, E., Münte, T. F., & Rodríguez-Fornells, A. (2012). Brain oscillatory activity associated with task switching and feedback processing. *Cognitive, Affective, & Behavioral Neuroscience*, *12*(1), 16–33. https://doi.org/10.3758/s13415-011-0075-5

Curşeu, P. L., & Schruijer, S. G. L. (2012). Decision Styles and Rationality. *Educational and Psychological Measurement*, *72*(6), 1053–1062. https://doi.org/10.1177/0013164412448066

Deen, O. M. T. A., Fan, S.-Z., & Shieh, J.-S. (2025). A Multimodal Deep Learning Approach to Intraoperative Nociception Monitoring: Integrating Electroencephalogram, Photoplethysmography, and Electrocardiogram. *Sensors*, *25*(4), 1150. https://doi.org/10.3390/s25041150

Desoete, A. (2008). Multi-method assessment of metacognitive skills in elementary school children: how you test is what you get. *Metacognition and Learning*, *3*(3), 189. https://doi.org/10.1007/s11409-008-9026-0

Diamond, A. (2013). Executive Functions. *Annual Review of Psychology*, *64*(1), 135–168. https://doi.org/10.1146/annurev-psych-113011-143750

Dias, N. M., Helsdingen, I. E., Lins, E. K. R. M. de, Etcheverria, C. E., Dechen, V. de A., Steffen, L., Cardoso, C. de O., & Lopes, F. M. (2023). Executive Functions Beyond the “Holy Trinity”: A Scoping Review. *Neuropsychology*, *38*(2), 107–125. https://doi.org/10.1037/neu0000922

Duncan, J. (2010). The multiple-demand (MD) system of the primate brain: mental programs for intelligent behaviour. *Trends in Cognitive Sciences*, *14*(4), 172–179. https://doi.org/10.1016/j.tics.2010.01.004

Duncan, P. K., & Bruwelheide, L. R. (1985). Feedback: Use and Possible Behavioral Functions. *Journal of Organizational Behavior Management*, *7*(3–4), 91–114. https://doi.org/10.1300/j075v07n03_06

Edwards, W. (1954). The theory of decision making. *Psychological Bulletin*, *51*(4), 380–417. https://doi.org/10.1037/h0053870

Ehrlinger, J., Readinger, W. O., & Kim, B. (2016). Decision-Making and Cognitive Biases. In *Encyclopedia of Mental Health (Second Edition)* (pp. 83–87). https://doi.org/10.1016/b978-0-12-397045-9.00206-8

Eidelman, S., Crandall, C. S., & Pattershall, J. (2009). The Existence Bias. *Journal of Personality and Social Psychology*, *97*(5), 765–775. https://doi.org/10.1037/a0017058

Engel, A. K., & Fries, P. (2010). Beta-band oscillations—signalling the status quo? *Current Opinion in Neurobiology*, *20*(2), 156–165. https://doi.org/10.1016/j.conb.2010.02.015

Engle, R. W. (2002). Working Memory Capacity as Executive Attention. *Current Directions in Psychological Science*, *11*(1), 19–23. https://doi.org/10.1111/1467-8721.00160

Ertl, M., Hildebrandt, M., Ourina, K., Leicht, G., & Mulert, C. (2013). Emotion regulation by cognitive reappraisal — The role of frontal theta oscillations. *NeuroImage*, *81*, 412–421. https://doi.org/10.1016/j.neuroimage.2013.05.044

Evans, J. St. B. T. (2008). Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition. *Annual Review of Psychology*, *59*(1), 255–278. https://doi.org/10.1146/annurev.psych.59.103006.093629

Danielmeier, C., & Ullsperger, M. (2011). Post-error adjustments. *Frontiers in psychology*, *2*, 233. https://doi.org/10.3389/fpsyg.2011.00233

Del Missier, F., Mäntylä, T., & Bruine de Bruin, W. (2010). Executive functions in decision making: An individual differences approach. *Thinking & Reasoning*, *16*(2), 69–97. https://doi.org/10.1080/13546781003630117

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*(2), 175–191. https://doi.org/10.3758/bf03193146

Ferdinand, N. K., Mecklinger, A., Kray, J., & Gehring, W. J. (2012). The Processing of Unexpected Positive Response Outcomes in the Mediofrontal Cortex. *The Journal of Neuroscience*, *32*(35), 12087–12092. https://doi.org/10.1523/jneurosci.1410-12.2012

Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American Psychologist*, *34*(10), 906–911. https://doi.org/10.1037/0003-066x.34.10.906

Fleming, S. M. (2023). Metacognition and Confidence: A Review and Synthesis. *Annual Review of Psychology*, *75*(1), 241–268. https://doi.org/10.1146/annurev-psych-022423-032425

Fleming, S. M., & Dolan, R. J. (2012). The neural basis of metacognitive ability. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1594), 1338–1349. https://doi.org/10.1098/rstb.2011.0417

Fleming, S. M., & Lau, H. C. (2014). How to measure metacognition. *Frontiers in Human Neuroscience*, *8*, 443. https://doi.org/10.3389/fnhum.2014.00443

Foster, P., & Skehan, P. (1996). The Influence of Planning and Task Type on Second Language Performance. *Studies in Second Language Acquisition*, *18*(3), 299–323. https://doi.org/10.1017/s0272263100015047

Fuster, J. M. (1993). Frontal lobes. *Current Opinion in Neurobiology*, *3*(2), 160–165. https://doi.org/10.1016/0959-4388(93)90204-c

Fuster, J. M. (1999). Chapter 22 Memory networks in the prefrontal cortex. *Progress in Brain Research*, *122*, 309–316. https://doi.org/10.1016/s0079-6123(08)62147-0

Gagnepain, P., Henson, R. N., & Anderson, M. C. (2014). Suppressing unwanted memories reduces their unconscious influence via targeted cortical inhibition. *Proceedings of the National Academy of Sciences*, *111*(13), E1310–E1319. https://doi.org/10.1073/pnas.1311468111

Gal, D. (2006). A psychological law of inertia and the illusion of loss aversion. *Judgment and Decision Making*, *1*(1), 23–32. https://doi.org/10.1017/s1930297500000322

Gambetti, E., Fabbri, M., Bensi, L., & Tonetti, L. (2008). A contribution to the Italian validation of the General Decision-making Style Inventory. *Personality and Individual Differences*, *44*(4), 842–852. https://doi.org/10.1016/j.paid.2007.10.017

García-Arch, J., Friedrich, S., Wu, X., Cucurell, D., & Fuentemilla, L. (2024). Beyond the Positivity Bias: The Processing and Integration of Self-Relevant Feedback Is Driven by Its Alignment With Pre-Existing Self-Views. *Cognitive Science*, *48*(11), e70017. https://doi.org/10.1111/cogs.70017

García-Arch, J., Sabio-Albert, M., & Fuentemilla, L. (2025). Selective Integration of Social Feedback Promotes a Stable and Positively Biased Self-Concept. *Scandinavian Journal of Psychology*. https://doi.org/10.1111/sjop.13113

Gascoine, L., Higgins, S., & Wall, K. (2017). The assessment of metacognition in children aged 4–16 years: a systematic review. *Review of Education*, *5*(1), 3–57. https://doi.org/10.1002/rev3.3077

Gibbons, P. T., & O'Brien, M. (2001). Socialisation and chief executive commitment to the status quo. *Irish Journal of Management*, *22*(2), 143–172.

Giorgetta, C., Grecucci, A., Zuanon, S., Perini, L., Balestrieri, M., Bonini, N., Sanfey, A. G., & Brambilla, P. (2012). Reduced Risk-Taking Behavior as a Trait Feature of Anxiety. *Emotion*, *12*(6), 1373–1383. https://doi.org/10.1037/a0029119

Goel, V., & Grafman, J. (1995). Are the frontal lobes implicated in "planning" functions? Interpreting data from the Tower of Hanoi. *Neuropsychologia*, *33*(5), 623–642. https://doi.org/10.1016/0028-3932(95)90866-p

Gola, M., Magnuski, M., Szumska, I., & Wróbel, A. (2013). EEG beta band activity is related to attention and attentional deficits in the visual performance of elderly subjects. *International Journal of Psychophysiology*, *89*(3), 334–341. https://doi.org/10.1016/j.ijpsycho.2013.05.007

Goldhacker, M., Rosengarth, K., Plank, T., & Greenlee, M. W. (2014). The effect of feedback on performance and brain activation during perceptual learning. *Vision Research*, *99*, 99–110. https://doi.org/10.1016/j.visres.2013.11.010

Goldman-Rakic, P. S. (1995). Cellular basis of working memory. *Neuron*, *14*(3), 477–485. https://doi.org/10.1016/0896-6273(95)90304-6

Goldstein, S., Naglieri, J. A., Princiotta, D., & Otero, T. M. (2013). *Handbook of Executive Functioning*. 3–12. https://doi.org/10.1007/978-1-4614-8106-5_1

Gonzalez, C., Dana, J., Koshino, H., & Just, M. (2005). The framing effect and risky decisions: Examining cognitive functions with fMRI. *Journal of Economic Psychology*, *26*(1), 1–20. https://doi.org/10.1016/j.joep.2004.08.004

Grafman, J. (2002). The Structured Event Complex and the Human Prefrontal Cortex. In D. T. Stuss & R. T. Knight (Eds.), *Principles of Frontal Lobe Function* (pp. 292–310). https://doi.org/10.1093/acprof:oso/9780195134971.003.0019

Gregory, S., & Sperling, D. R. (1994). Assessing Metacognitive Awareness. *Contemporary Educational Psychology*, *19*(4), 460–475. https://doi.org/10.1006/ceps.1994.1033

Griebling, J., Minshew, N. J., Bodner, K., Libove, R., Bansal, R., Konasale, P., Keshavan, M. S., & Hardan, A. (2010). Dorsolateral Prefrontal Cortex Magnetic Resonance Imaging Measurements and Cognitive Performance in Autism. *Journal of Child Neurology*, *25*(7), 856–863. https://doi.org/10.1177/0883073809351313

Guevara, M. Á., González, M. H., Martínez, L. E. R., & Aguirre, F. A. R. (2013). Performance of the Towers of Hanoi task and cortical electroencephalographic power changes associated with infancy, adolescence, and early adulthood. *Experimental Brain Research*, *231*(3), 315–324. https://doi.org/10.1007/s00221-013-3693-z

Guido, G., Peluso, A. M., Capestro, M., & Miglietta, M. (2015). An Italian version of the 10-item Big Five Inventory: An application to hedonic and utilitarian shopping values. *Personality and Individual Differences*, *76*, 135–140. https://doi.org/10.1016/j.paid.2014.11.053

Guttman, Z., Moeller, S. J., & London, E. D. (2018). Neural underpinnings of maladaptive decision-making in addictions. *Pharmacology Biochemistry and Behavior*, *164*, 84–98. https://doi.org/10.1016/j.pbb.2017.06.014

HajiHosseini, A., Rodríguez-Fornells, A., & Marco-Pallarés, J. (2012). The role of beta-gamma oscillations in unexpected rewards processing. *NeuroImage*, *60*(3), 1678–1685. https://doi.org/10.1016/j.neuroimage.2012.01.125

Hajcak, G. (2012). What we've learned from mistakes: Insights from error-related brain activity. *Current Directions in Psychological Science*, *21*(2), 101-106. https://doi.org/10.1177/0963721412436809

Hanslmayr, S., Gross, J., Klimesch, W., & Shapiro, K. L. (2011). The role of alpha oscillations in temporal attention. *Brain Research Reviews*, *67*(1–2), 331–343. https://doi.org/10.1016/j.brainresrev.2011.04.002

Hanslmayr, S., Matuschek, J., & Fellner, M.-C. (2014). Entrainment of Prefrontal Beta Oscillations Induces an Endogenous Echo and Impairs Memory Formation. *Current Biology*, *24*(8), 904–909. https://doi.org/10.1016/j.cub.2014.03.007

Happaney, K., Zelazo, P. D., & Stuss, D. T. (2004). Development of orbitofrontal function: Current themes and future directions. *Brain and Cognition*, *55*(1), 1–10. https://doi.org/10.1016/j.bandc.2004.01.001

Harmony, T. (2013). The functional significance of delta oscillations in cognitive processing. *Frontiers in Integrative Neuroscience*, *7*, 83. https://doi.org/10.3389/fnint.2013.00083

Harmony, T., Fernández, T., Silva, J., Bernal, J., Díaz-Comas, L., Reyes, A., Marosi, E., Rodríguez, M., & Rodríguez, M. (1996). EEG delta activity: an indicator of attention to internal processing during performance of mental tasks. *International Journal of Psychophysiology*, *24*(1–2), 161–171. https://doi.org/10.1016/s0167-8760(96)00053-0

Hattie, J., & Timperley, H. (2007). The Power of Feedback. *Review of Educational Research*, *77*(1), 81–112. https://doi.org/10.3102/003465430298487

Head, D., Raz, N., Gunning-Dixon, F., Williamson, A., & Acker, J. D. (2002). Age-Related Differences in the Course of Cognitive Skill Acquisition: The Role of Regional Cortical Shrinkage and Cognitive Resources. *Psychology and Aging*, *17*(1), 72–84. https://doi.org/10.1037/0882-7974.17.1.72

Herrmann, C. S., Strüber, D., Helfrich, R. F., & Engel, A. K. (2016). EEG oscillations: From correlation to causality. *International Journal of Psychophysiology*, *103*, 12–21. https://doi.org/10.1016/j.ijpsycho.2015.02.003

Hewig, J., Trippe, R., Hecht, H., Coles, M. G., Holroyd, C. B., & Miltner, W. H. (2007). Decision-making in blackjack: an electrophysiological analysis. *Cerebral Cortex*, *17*(4), 865-877. https://doi.org/10.1093/cercor/bhk040

Hikosaka, K., & Watanabe, M. (2000). Delay Activity of Orbital and Lateral Prefrontal Neurons of the Monkey Varying with Different Rewards. *Cerebral Cortex*, *10*(3), 263–271. https://doi.org/10.1093/cercor/10.3.263

Hills, P., & Argyle, M. (2001). Emotional stability as a major dimension of happiness. *Personality and Individual Differences*, *31*(8), 1357–1364. https://doi.org/10.1016/s0191-8869(00)00229-4

Hobson, J. A., & Pace-Schott, E. F. (2002). The cognitive neuroscience of sleep: neuronal systems, consciousness and learning. *Nature Reviews Neuroscience*, *3*(9), 679–693. https://doi.org/10.1038/nrn915

Hodgkinson, G. P. (1997). Cognitive Inertia in a Turbulent Market: the Case of UK Residential Estate Agents. *Journal of Management Studies*, *34*(6), 921–945. https://doi.org/10.1111/1467-6486.00078

Hodgkinson, G. P., & Wright, G. (2002). Confronting Strategic Inertia in a Top Management Team: Learning from Failure. *Organization Studies*, *23*(6), 949–977. https://doi.org/10.1177/0170840602236014

Holroyd, C. B., & Coles, M. G. H. (2002). The Neural Basis of Human Error Processing: Reinforcement Learning, Dopamine, and the Error-Related Negativity. *Psychological Review*, *109*(4), 679–709. https://doi.org/10.1037/0033-295x.109.4.679

Holroyd, C. B., Pakzad-Vaezi, K. L., & Krigolson, O. E. (2008). The feedback correct-related positivity: Sensitivity of the event-related brain potential to unexpected positive feedback. *Psychophysiology*, *45*(5), 688–697. https://doi.org/10.1111/j.1469-8986.2008.00668.x

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

Huster, R. J., Enriquez-Geppert, S., Lavallee, C. F., Falkenstein, M., & Herrmann, C. S. (2013). Electroencephalography of response inhibition tasks: Functional networks and cognitive contributions. *International Journal of Psychophysiology*, *87*(3), 217–233. https://doi.org/10.1016/j.ijpsycho.2012.08.001

Immordino-Yang, M. H., & Damasio, A. (2007). We Feel, Therefore We Learn: The Relevance of Affective and Social Neuroscience to Education. *Mind, Brain, and Education*, *1*(1), 3–10. https://doi.org/10.1111/j.1751-228x.2007.00004.x

Jasper, H. H. (1958). Ten-twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology*, *10*, 371–375.

Johnson, J. G., & Busemeyer, J. R. (2010). Decision making under risk and uncertainty. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*(5), 736–749. https://doi.org/10.1002/wcs.76

Jurado, M. B., & Rosselli, M. (2007). The Elusive Nature of Executive Functions: A Review of our Current Understanding. *Neuropsychology Review*, *17*(3), 213–233. https://doi.org/10.1007/s11065-007-9040-z

Kahneman. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.

Kahneman, D. (2003). A Perspective on Judgment and Choice. *American Psychologist*, *58*(9), 697–720. https://doi.org/10.1037/0003-066x.58.9.697

Kahneman, D., & Tversky, A. (2013). Prospect Theory: An Analysis of Decision Under Risk. In *Handbook of the Fundamentals of Financial Decision Making* (Vol. 4, pp. 99–127). World Scientific Publishing Co Pte Ltd. https://doi.org/10.1142/9789814417358_0006

Kaller, C. P., Rahm, B., Spreer, J., Weiller, C., & Unterrainer, J. M. (2011). Dissociable Contributions of Left and Right Dorsolateral Prefrontal Cortex in Planning. *Cerebral Cortex*, *21*(2), 307–317. https://doi.org/10.1093/cercor/bhq096

Kamarajan, C., Porjesz, B., Jones, K. A., Choi, K., Chorlian, D. B., Padmanabhapillai, A., Rangaswamy, M., Stimus, A. T., & Begleiter, H. (2004). The role of brain oscillations as functional correlates of cognitive systems: a study of frontal inhibitory control in alcoholism. *International Journal of Psychophysiology*, *51*(2), 155–180. https://doi.org/10.1016/j.ijpsycho.2003.09.004

Karr, J. E., Areshenkoff, C. N., Rast, P., Hofer, S. M., Iverson, G. L., & Garcia-Barrera, M. A. (2018). The Unity and Diversity of Executive Functions: A Systematic Review and Re-Analysis of Latent Variable Studies. *Psychological Bulletin*, *144*(11), 1147–1185. https://doi.org/10.1037/bul0000160

Kepecs, A., & Mainen, Z. F. (2012). A computational framework for the study of confidence in humans and animals. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *367*(1594), 1322–1337. https://doi.org/10.1098/rstb.2012.0037

Kerns, J. G. (2006). Anterior cingulate and prefrontal cortex activity in an FMRI study of trial-to-trial adjustments on the Simon task. *NeuroImage*, *33*(1), 399–405. https://doi.org/10.1016/j.neuroimage.2006.06.012

Kerns, J. G., Cohen, J. D., III, A. W. M., Cho, R. Y., Stenger, V. A., & Carter, C. S. (2004). Anterior Cingulate Conflict Monitoring and Adjustments in Control. *Science*, *303*(5660), 1023–1026. https://doi.org/10.1126/science.1089910

Khader, P. H., Jost, K., Ranganath, C., & Rösler, F. (2010). Theta and alpha oscillations during working-memory maintenance predict successful long-term memory encoding. *Neuroscience Letters*, *468*(3), 339–343. https://doi.org/10.1016/j.neulet.2009.11.028

Kilavik, B. E., Zaepffel, M., Brovelli, A., MacKay, W. A., & Riehle, A. (2013). The ups and downs of beta oscillations in sensorimotor cortex. *Experimental Neurology*, *245*, 15–26. https://doi.org/10.1016/j.expneurol.2012.09.014

Kimura, K., Chitose, R., & Yokosawa, K. (2016). Alpha-band Amplitude During Memory Encoding Is an Index of Memory Performance. *Advanced Biomedical Engineering*, *5*(0), 43. https://doi.org/10.14326/abe.5.43

Klein, H. J. (1989). An Integrated Control Theory Model of Work Motivation. *Academy of Management Review*, *14*(2), 150–172. https://doi.org/10.5465/amr.1989.4282072

Klimesch, W. (1997). EEG-alpha rhythms and memory processes. *International Journal of Psychophysiology*, *26*(1–3), 319–340. https://doi.org/10.1016/s0167-8760(97)00773-3

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition–timing hypothesis. *Brain Research Reviews*, *53*(1), 63–88. https://doi.org/10.1016/j.brainresrev.2006.06.003

Kluger, & DeNisi. (1996). The effects of feedback interventions on performance: a historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin*, *2*(119), 254–284.

Kluwe-Schiavon, B., Viola, T. W., Sanvicente-Vieira, B., Malloy-Diniz, L. F., & Grassi-Oliveira, R. (2017). Balancing Automatic-Controlled Behaviors and Emotional-Salience States: A Dynamic Executive Functioning Hypothesis. *Frontiers in Psychology*, *7*, 2067. https://doi.org/10.3389/fpsyg.2016.02067

Knutson, B., Westdorp, A., Kaiser, E., & Hommer, D. (2000). FMRI Visualization of Brain Activity during a Monetary Incentive Delay Task. *NeuroImage*, *12*(1), 20–27. https://doi.org/10.1006/nimg.2000.0593

Knyazev, G. G. (2007). Motivation, emotion, and their inhibitory control mirrored in brain oscillations. *Neuroscience & Biobehavioral Reviews*, *31*(3), 377–395. https://doi.org/10.1016/j.neubiorev.2006.10.004

Knyazev, G. G. (2012). EEG delta oscillations as a correlate of basic homeostatic and motivational processes. *Neuroscience & Biobehavioral Reviews*, *36*(1), 677–695. https://doi.org/10.1016/j.neubiorev.2011.10.002

Knyazev, G. G. (2013). EEG Correlates of Self-Referential Processing. *Frontiers in Human Neuroscience*, *7*, 264. https://doi.org/10.3389/fnhum.2013.00264

Knyazev, G. G., Savostyanov, A. N., Bocharov, A. V., Dorosheva, E. A., Tamozhnikov, S. S., & Saprigyn, A. E. (2015). Oscillatory correlates of autobiographical memory. *International Journal of Psychophysiology*, *95*(3), 322–332. https://doi.org/10.1016/j.ijpsycho.2014.12.006

Knyazev, G. G., Slobodskoj-Plusnin, J. Y., & Bocharov, A. V. (2009). Event-related delta and theta synchronization during explicit and implicit emotion processing. *Neuroscience*, *164*(4), 1588–1600. https://doi.org/10.1016/j.neuroscience.2009.09.057

Kobza, S., Ferrea, S., Schnitzler, A., Pollok, B., Südmeyer, M., & Bellebaum, C. (2012). Dissociation between Active and Observational Learning from Positive and Negative Feedback in Parkinsonism. *PLoS ONE*, *7*(11), e50250. https://doi.org/10.1371/journal.pone.0050250

Korotkova, T., Ponomarenko, A., Monaghan, C. K., Poulter, S. L., Cacucci, F., Wills, T., Hasselmo, M. E., & Lever, C. (2018). Reconciling the different faces of hippocampal theta: The role of theta oscillations in cognitive, emotional and innate behaviors. *Neuroscience & Biobehavioral Reviews*, *85*, 65–80. https://doi.org/10.1016/j.neubiorev.2017.09.004

Krakauer, J. W., Ghazanfar, A. A., Gomez-Marin, A., MacIver, M. A., & Poeppel, D. (2017). Neuroscience Needs Behavior: Correcting a Reductionist Bias. *Neuron*, *93*(3), 480–490. https://doi.org/10.1016/j.neuron.2016.12.041

Krawczyk, D. C. (2002). Contributions of the prefrontal cortex to the neural basis of human decision making. *Neuroscience & Biobehavioral Reviews*, *26*(6), 631–664. https://doi.org/10.1016/s0149-7634(02)00021-0

Laureiro-Martínez, D., & Brusoni, S. (2018). Cognitive flexibility and adaptive decision-making: Evidence from a laboratory study of expert decision makers. *Strategic Management Journal*, *39*(4), 1031–1058. https://doi.org/10.1002/smj.2774

Lee, D., & Seo, H. (2007). Mechanisms of Reinforcement Learning and Decision Making in the Primate Dorsolateral Prefrontal Cortex. *Annals of the New York Academy of Sciences*, *1104*(1), 108–122. https://doi.org/10.1196/annals.1390.007

Levine, L. J., Schmidt, S., Kang, H. S., & Tinti, C. (2012). Remembering the silver lining: Reappraisal and positive bias in memory for emotion. *Cognition and Emotion*, *26*(5), 871–884. https://doi.org/10.1080/02699931.2011.625403

Lezak, M. D. (1982). The problem of assessing executive functions. *International Journal of Psychology*, *17*(1–4), 281–297. https://doi.org/10.1080/00207598208247445

Lezak, M. D. (2004). *Neuropsychological assessment*. Oxford University Press, USA.

Lezak, M. D., Howieson, D. B., Bigler, E. D., & Tranel, D. (2012). *Neuropsychological assessment* (5th ed.). Oxford University Press.

Li, P., Baker, T. E., Warren, C., & Li, H. (2016). Oscillatory profiles of positive, negative and neutral feedback stimuli during adaptive decision making. *International Journal of Psychophysiology*, *107*, 37–43. https://doi.org/10.1016/j.ijpsycho.2016.06.018

Liang, L.-Y., Shewokis, P. A., & Getchell, N. (2016). Brain Activation in the Prefrontal Cortex during Motor and Cognitive Tasks in Adults. *Journal of Behavioral and Brain Science*, *6*(12), 463–474. https://doi.org/10.4236/jbbs.2016.612042

Lipnevich, A. A., & Panadero, E. (2021). A Review of Feedback Models and Theories: Descriptions, Definitions, and Conclusions. *Frontiers in Education*, *6*, 720195. https://doi.org/10.3389/feduc.2021.720195

Locke, E. A., & Latham, G. P. (1990). Work Motivation and Satisfaction: Light at the End of the Tunnel. *Psychological Science*, *1*(4), 240–246. https://doi.org/10.1111/j.1467-9280.1990.tb00207.x

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as Feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Löffler, C., Frischkorn, G. T., Hagemann, D., Sadus, K., & Schubert, A.-L. (2024). The common factor of executive functions measures nothing but speed of information uptake. *Psychological Research*, *88*(4), 1092–1114. https://doi.org/10.1007/s00426-023-01924-7

Lord, R. G., & Kernan, M. C. (1987). Scripts as Determinants of Purposeful Behavior in Organizations. *Academy of Management Review*, *12*(2), 265–277. https://doi.org/10.5465/amr.1987.4307831

Luft, C. D. B. (2014). Learning from feedback: The neural mechanisms of feedback processing facilitating better performance. *Behavioural Brain Research*, *261*, 356–368. https://doi.org/10.1016/j.bbr.2013.12.043

Lundqvist, M., Rose, J., Herman, P., Brincat, S. L., Buschman, T. J., & Miller, E. K. (2016). Gamma and Beta Bursts Underlie Working Memory. *Neuron*, *90*(1), 152–164. https://doi.org/10.1016/j.neuron.2016.02.028

Luo, T., & Liu, C. (2023). The impact of feedback on metacognition: Enhancing in easy tasks, impeding in difficult ones. *Consciousness and Cognition*, *116*, 103601. https://doi.org/10.1016/j.concog.2023.103601

Luria, A. R. (1973). The frontal lobes and the regulation of behavior. In *Psychophysiology of the Frontal Lobes* (pp. 3–26). Academic Press. https://doi.org/10.1016/b978-0-12-564340-5.50006-8

Luu, P., Tucker, D. M., & Makeig, S. (2004). Frontal midline theta and the error-related negativity: neurophysiological mechanisms of action regulation. *Clinical Neurophysiology*, *115*(8), 1821–1835. https://doi.org/10.1016/j.clinph.2004.03.031

Maner, J. K., Gailliot, M. T., Butz, D. A., & Peruche, B. M. (2007). Power, Risk, and the Status Quo. *Personality and Social Psychology Bulletin*, *33*(4), 451–462. https://doi.org/10.1177/0146167206297405

Mangiapanello, K. A., & Hemmes, N. S. (2015). An Analysis of Feedback from a Behavior Analytic Perspective. *The Behavior Analyst*, *38*(1), 51–75. https://doi.org/10.1007/s40614-014-0026-x

Marco-Pallarés, J., Müller, S. V., & Münte, T. F. (2007). Learning by doing: an fMRI study of feedback-related brain activations. *NeuroReport*, *18*(14), 1423–1426. https://doi.org/10.1097/wnr.0b013e3282e9a58c

Marco-Pallarés, J., Münte, T. F., & Rodríguez-Fornells, A. (2015). The role of high-frequency oscillatory activity in reward processing and learning. *Neuroscience & Biobehavioral Reviews*, *49*, 1–7. https://doi.org/10.1016/j.neubiorev.2014.11.014

Marom, S., Meir, R., Braun, E., Gal, A., Kermany, E., & Eytan, D. (2009). On the precarious path of reverse neuro-engineering. *Frontiers in Computational Neuroscience*, *3*, 5. https://doi.org/10.3389/neuro.10.005.2009

McClelland, J. L. (2001). Cognitive Neuroscience. In *International Encyclopedia of the Social & Behavioral Sciences* (pp. 2133–2140). https://doi.org/10.1016/b0-08-043076-7/03406-9

McCloskey, G., Perkins, L. A., & Divner, B. V. (2011). *Assessment and Intervention for Executive Function Difficulties*. https://doi.org/10.4324/9780203893753

McClure, S. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2004). Separate Neural Systems Value Immediate and Delayed Monetary Rewards. *Science*, *306*(5695), 503–507. https://doi.org/10.1126/science.1100907

Menon, V., Adleman, N. E., White, C. D., Glover, G. H., & Reiss, A. L. (2001). Error-related brain activation during a Go/NoGo response inhibition task. *Human brain mapping*, *12*(3), 131-143. https://doi.org/10.1002/1097-0193(200103)12:3%3C131::AID-HBM1010%3E3.0.CO;2-C

Merker, B. (2013). Cortical gamma oscillations: the functional key is activation, not cognition. *Neuroscience & Biobehavioral Reviews*, *37*(3), 401–417. https://doi.org/10.1016/j.neubiorev.2013.01.013

Michalareas, G., Vezoli, J., van Pelt, S., Schoffelen, J.-M., Kennedy, H., & Fries, P. (2016). Alpha-Beta and Gamma Rhythms Subserve Feedback and Feedforward Influences among Human Visual Cortical Areas. *Neuron*, *89*(2), 384–397. https://doi.org/10.1016/j.neuron.2015.12.018

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*(1), 167–202. https://doi.org/10.1146/annurev.neuro.24.1.167

Miller, E. K., Lundqvist, M., & Bastos, A. M. (2018). Working Memory 2.0. *Neuron*, *100*(2), 463–475. https://doi.org/10.1016/j.neuron.2018.09.023

Miltenberger. (1997). *Behavior modification: Principles and procedures*. Brooks/Cole Publishing Company.

Mitani, K., Rathnayake, N., Rathnayake, U., Dang, T. L., & Hoshino, Y. (2022). Brain Activity Associated with the Planning Process during the Long-Time Learning of the Tower of Hanoi (ToH) Task: A Pilot Study. *Sensors*, *22*(21), 8283. https://doi.org/10.3390/s22218283

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and Their Contributions to Complex "Frontal Lobe" Tasks: A Latent Variable Analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734

Miyapuram, K. P., & Pammi, V. S. C. (2013). Chapter 14 Understanding decision neuroscience: A multidisciplinary perspective and neural substrates. *Progress in Brain Research*, *202*, 239–266. https://doi.org/10.1016/b978-0-444-62604-2.00014-9

Mohr, P. N. C., Biele, G., & Heekeren, H. R. (2010). Neural Processing of Risk. *The Journal of Neuroscience*, *30*(19), 6613–6619. https://doi.org/10.1523/jneurosci.0003-10.2010

Morales, J., Lau, H., & Fleming, S. M. (2018). Domain-general and domain-specific patterns of activity supporting metacognition in human prefrontal cortex. *Journal of Neuroscience*, *38*(14), 3534-3546. https://doi.org/10.1523/JNEUROSCI.2360-17.2018

Morelli, M., Casagrande, M., & Forte, G. (2022). Decision Making: a Theoretical Review. *Integrative Psychological and Behavioral Science*, *56*(3), 609–629. https://doi.org/10.1007/s12124-021-09669-x

Mulholland, T. B. (1972). Occipital alpha revisited. *Psychological Bulletin*, *78*(3), 176–182. https://doi.org/10.1037/h0032962

Müller-Putz, G. R. (2020). Electroencephalography. In *Handbook of Clinical Neurology* (Vol. 168, pp. 249–262). https://doi.org/10.1016/b978-0-444-63934-9.00018-4

Murphy, P. R., Robertson, I. H., Harty, S., & O'Connell, R. G. (2015). Neural evidence accumulation persists after choice to inform metacognitive judgments. *elife*, *4*, e11946. https://doi.org/10.7554/eLife.11946

Nenkov, G. Y., Morrin, M., Ward, A., Schwartz, B., & Hulland, J. (2008). A short form of the Maximization Scale: Factor structure, reliability and validity studies. *Judgment and Decision Making*, *3*(5), 371–388. https://doi.org/10.1017/s1930297500000395

Neumann, J. V., & Morgenstern, O. (1947). *Theory of games and economic behavior, 2nd rev. ed.* Princeton University Press.

Neuper, C., & Pfurtscheller, G. (2001). Event-related dynamics of cortical rhythms: frequency-specific features and functional correlates. *International Journal of Psychophysiology*, *43*(1), 41–58. https://doi.org/10.1016/s0167-8760(01)00178-7

Nieuwenhuis, S., Slagter, H. A., Geusau, N. J. A. V., Heslenfeld, D. J., & Holroyd, C. B. (2005). Knowing good from bad: differential activation of human cortical areas by positive and negative outcomes. *European Journal of Neuroscience*, *21*(11), 3161–3168. https://doi.org/10.1111/j.1460-9568.2005.04152.x

Norman, D. A., & Shallice, T. (1986). *Consciousness and Self-Regulation, Advances in Research and Theory* (Vol. 4, pp. 1–18). https://doi.org/10.1007/978-1-4757-0629-1_1

Norris, C. J., Leaf, P. T., & Fenn, K. M. (2019). Negativity bias in false memory: moderation by neuroticism after a delay. *Cognition and Emotion*, *33*(4), 737–753. https://doi.org/10.1080/02699931.2018.1496068

Nowak, A., Vallacher, R. R., Tesser, A., & Borkowski, W. (2000). Society of self: The emergence of collective properties in self-structure. *Psychological Review*, *107*(1), 39–61.

Nunez, P. L., & Williamson, S. J. (1996). Neocortical Dynamics and Human EEG Rhythms. *Physics Today*, *49*(4), 57–57. https://doi.org/10.1063/1.2807585

Olvet, D. M., & Hajcak, G. (2008). The error-related negativity (ERN) and psychopathology: Toward an endophenotype. *Clinical psychology review*, *28*(8), 1343-1354. https://doi.org/10.1016/j.cpr.2008.07.003

Otero, T. M., & Barker, L. A. (2014). The Frontal Lobes and Executive Functioning. In S. Goldstein & J. Naglieri (Eds.), *Handbook of Executive Functioning* (pp. 29–44). Springer. https://doi.org/10.1007/978-1-4614-8106-5_3

Overbeek, T. J., Nieuwenhuis, S., & Ridderinkhof, K. R. (2005). Dissociable components of error processing: On the functional significance of the Pe vis-à-vis the ERN/Ne. *Journal of psychophysiology*, *19*(4), 319-329. https://doi.org/10.1027/0269-8803.19.4.319

Pace-Schott, E. F., Amole, M. C., Aue, T., Balconi, M., Bylsma, L. M., Critchley, H., Demaree, H. A., Friedman, B. H., Gooding, A. E. K., Gosseries, O., Jovanovic, T., Kirby, L. A. J., Kozlowska, K., Laureys, S., Lowe, L., Magee, K., Marin, M.-F., Merner, A. R., Robinson, J. L., … VanElzakker, M. B. (2019). Physiological feelings. *Neuroscience & Biobehavioral Reviews*, *103*, 267–304. https://doi.org/10.1016/j.neubiorev.2019.05.002

Panidi, K., Vorobiova, A. N., Feurra, M., & Klucharev, V. (2022). Dorsolateral prefrontal cortex plays causal role in probability weighting during risky choice. *Scientific Reports*, *12*(1), 16115. https://doi.org/10.1038/s41598-022-18529-6

Payne, L., Guillory, S., & Sekuler, R. (2013). Attention-modulated Alpha-band Oscillations Protect against Intrusion of Irrelevant Information. *Journal of Cognitive Neuroscience*, *25*(9), 1463–1476. https://doi.org/10.1162/jocn_a_00395

Peterson, N. (1982). Feedback is Not a New Principle of Behavior. *The Behavior Analyst*, *5*(1), 101–102. https://doi.org/10.1007/bf03393144

Pintrich, P. R. (2000). The Role of Goal Orientation in Self-Regulated Learning. In *Handbook of Self-Regulation* (pp. 451–502). https://doi.org/10.1016/b978-012109890-2/50043-3

Pintrich, P. R., Smith, D. A. F., Garcia, T., & Mckeachie, W. J. (1993). Reliability and Predictive Validity of the Motivated Strategies for Learning Questionnaire (Mslq). *Educational and Psychological Measurement*, *53*(3), 801–813. https://doi.org/10.1177/0013164493053003024

Pizzagalli, D. A. (2007). Electroencephalography and high-density electrophysiological source localization. In I. J. T. Cacioppo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (Vol. 3, pp. 56–84). Cambridge University Press.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019

Posner, M. I., & Snyder, C. R. R. (1975). Attention And Cognitive Control 1. In *Information Processing and Cognition* (pp. 55–85). https://doi.org/10.4324/9781032722450-4

Putman, P. (2011). Resting state EEG delta–beta coherence in relation to anxiety, behavioral inhibition, and selective attentional processing of threatening stimuli. *International Journal of Psychophysiology*, *80*(1), 63–68. https://doi.org/10.1016/j.ijpsycho.2011.01.011

Qiu, L., Su, J., Ni, Y., Bai, Y., Zhang, X., Li, X., & Wan, X. (2018). The neural system of metacognition accompanying decision-making in the prefrontal cortex. *PLoS Biology*, *16*(4), e2004037. https://doi.org/10.1371/journal.pbio.2004037

Raes, A. M. L., Heijltjes, M. G., Glunk, U., & Roe, R. A. (2011). The Interface of the Top Management Team and Middle Managers: A Process Model. *Academy of Management Review*, *36*(1), 102–126. https://doi.org/10.5465/amr.2009.0088

Rabbitt, P. M. (1966). Errors and error correction in choice-response tasks. *Journal of Experimental Psychology, 71*(2), 264–272. https://doi.org/10.1037/h0022853

Ratti, E., Waninger, S., Berka, C., Ruffini, G., & Verma, A. (2017). Comparison of Medical and Consumer Wireless EEG Systems for Use in Clinical Trials. *Frontiers in Human Neuroscience*, *11*, 398. https://doi.org/10.3389/fnhum.2017.00398

Ray, W. J., & Cole, H. W. (1985a). EEG activity during cognitive processing: Influence of attentional factors. *International Journal of Psychophysiology*, *3*(1), 43–48. https://doi.org/10.1016/0167-8760(85)90018-2

Ray, W. J., & Cole, H. W. (1985b). EEG Alpha Activity Reflects Attentional Demands, and Beta Activity Reflects Emotional and Cognitive Processes. *Science*, *228*(4700), 750–752. https://doi.org/10.1126/science.3992243

Reyna, V. F. (2004). How People Make Decisions That Involve Risk. *Current Directions in Psychological Science*, *13*(2), 60–66. https://doi.org/10.1111/j.0963-7214.2004.00275.x

Ridderinkhof, K. R., Ullsperger, M., Crone, E. A., & Nieuwenhuis, S. (2004). The Role of the Medial Frontal Cortex in Cognitive Control. *Science*, *306*(5695), 443–447. https://doi.org/10.1126/science.1100301

Rolls, E. T. (2023). Emotion, motivation, decision-making, the orbitofrontal cortex, anterior cingulate cortex, and the amygdala. *Brain Structure and Function*, *228*(5), 1201–1257. https://doi.org/10.1007/s00429-023-02644-9

Rovelli, K., & Allegretta, R. A. (2023). Framing decision-making: the role of executive functions, cognitive bias and reward. *Neuropsychological Trends*, *33*, 37–50. https://doi.org/10.7358/neur-2023-033-rove

Ruiz-Díaz, M., Hernández-González, M., Guevara, M. A., Amezcua, C., & Ågmo, A. (2012). Prefrontal EEG Correlation During Tower of Hanoi and WCST Performance: Effect of Emotional Visual Stimuli. *The Journal of Sexual Medicine*, *9*(10), 2631–2640. https://doi.org/10.1111/j.1743-6109.2012.02782.x

Ruocco, A. C., Rodrigo, A. H., Lam, J., Domenico, S. I. D., Graves, B., & Ayaz, H. (2014). A problem-solving task specialized for functional neuroimaging: validation of the Scarborough adaptation of the Tower of London (S-TOL) using near-infrared spectroscopy. *Frontiers in Human Neuroscience*, *8*, 185. https://doi.org/10.3389/fnhum.2014.00185

Sadato, N., Nakamura, S., Oohashi, T., Nishina, E., Fuwamoto, Y., Waki, A., & Yonekura, Y. (1998). Neural networks for generation and suppression of alpha rhythm: a PET study. *Neuroreport*, *9*(5), 893–897.

Salehinejad, M. A., Ghanavati, E., Rashid, M. H. A., & Nitsche, M. A. (2021). Hot and cold executive functions in the brain: A prefrontal-cingular network. *Brain and Neuroscience Advances*, *5*, 23982128211007769. https://doi.org/10.1177/23982128211007769

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59. https://doi.org/10.1007/bf00055564

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

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: A possible function of EEG theta oscillations. *Neuroscience & Biobehavioral Reviews*, *34*(7), 1015–1022. https://doi.org/10.1016/j.neubiorev.2009.12.006

Sauseng, P., Tschentscher, N., & Biel, A. L. (2019). Be Prepared: Tune to FM-Theta for Cognitive Control. *Trends in Neurosciences*, *42*(5), 307–309. https://doi.org/10.1016/j.tins.2019.02.006

Schacter, D. L., Guerin, S. A., & Jacques, P. L. St. (2011). Memory distortion: an adaptive perspective. *Trends in Cognitive Sciences*, *15*(10), 467–474. https://doi.org/10.1016/j.tics.2011.08.004

Scheres, A., & Sanfey, A. G. (2006). Individual differences in decision making: Drive and reward responsiveness affect strategic bargaining in economic games. *Behavioral and Brain Functions*, *2*(1), 35. https://doi.org/10.1186/1744-9081-2-35

Schraw, G., Crippen, K. J., & Hartley, K. (2006). Promoting Self-Regulation in Science Education: Metacognition as Part of a Broader Perspective on Learning. *Research in Science Education*, *36*(1–2), 111–139. https://doi.org/10.1007/s11165-005-3917-8

Schreiner, T., Lehmann, M., & Rasch, B. (2015). Auditory feedback blocks memory benefits of cueing during sleep. *Nature Communications*, *6*(1), 8729. https://doi.org/10.1038/ncomms9729

Schuepbach, D., Merlo, M. C. G., Goenner, F., Staikov, I., Mattle, H. P., Dierks, T., & Brenner, H. D. (2002). Cerebral hemodynamic response induced by the Tower of Hanoi puzzle and the

Wisconsin Card Sorting test. *Neuropsychologia*, *40*(1), 39–53. https://doi.org/10.1016/s0028-3932(01)00074-4

Schürmann, M., & Başar, E. (2001). Functional aspects of alpha oscillations in the EEG. *International Journal of Psychophysiology*, *39*(2–3), 151–158. https://doi.org/10.1016/s0167-8760(00)00138-0

Scott, S. G., & Bruce, R. A. (1995). Decision-Making Style: The Development and Assessment of a New Measure. *Educational and Psychological Measurement*, *55*(5), 818–831. https://doi.org/10.1177/0013164495055005017

Sedikides, C., & Green, J. D. (2004). What I Don't Recall Can't Hurt Me: Information Negativity Versus Information Inconsistency As Determinants of Memorial Self-defense. *Social Cognition*, *22*(1), 4–29. https://doi.org/10.1521/soco.22.1.4.30987

Sedikides, C., & Green, J. D. (2006). The mnemic neglect model: Experimental demonstrations of inhibitory repression in normal adults. *Behavioral and Brain Sciences*, *29*(5), 532–533. https://doi.org/10.1017/s0140525x06449116

Shallice, T. (2002). Fractionation of the Supervisory System. In D. T. Stuss & R. T. Knight (Eds.), *Principles of Frontal Lobe Function* (pp. 261–277). https://doi.org/10.1093/acprof:oso/9780195134971.003.0017

Sharfman, M. P., & Jr, J. W. D. (1997). Flexibility in Strategic Decision Making: Informational and Ideological Perspectives. *Journal of Management Studies*, *34*(2), 191–217. https://doi.org/10.1111/1467-6486.00048

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The Expected Value of Control: An Integrative Theory of Anterior Cingulate Cortex Function. *Neuron*, *79*(2), 217–240. https://doi.org/10.1016/j.neuron.2013.07.007

Shin, H., Law, R., Tsutsui, S., Moore, C. I., & Jones, S. R. (2017). The rate of transient beta frequency events predicts behavior across tasks and species. *eLife*, *6*, e29086. https://doi.org/10.7554/elife.29086

Shuai, L., Daley, D., Wang, Y.-F., Zhang, J.-S., Kong, Y.-T., Tan, X., & Ji, N. (2017). Executive Function Training for Children with Attention Deficit Hyperactivity Disorder. *Chinese Medical Journal*, *130*(5), 549–558. https://doi.org/10.4103/0366-6999.200541

Siegel, M., Donner, T. H., & Engel, A. K. (2012). Spectral fingerprints of large-scale neuronal interactions. *Nature Reviews Neuroscience*, *13*(2), 121–134. https://doi.org/10.1038/nrn3137

Silva, V. P. da, Carthery-Goulart, M. T., & Lukasova, K. (2024). Unity and Diversity Model of Executive Functions: State of the Art and Issues to Be Resolved. *Psychology & Neuroscience*, *17*(4), 253–281. https://doi.org/10.1037/pne0000349

Silver, W. S., & Mitchell, T. R. (1990). The status quo tendency in decision making. *Organizational Dynamics*, *18*(4), 34–46. https://doi.org/10.1016/0090-2616(90)90055-t

Singer, W. (1993). Synchronization of cortical activity and its putative role in information processing and learning. *Annual Review of Physiology*, *55*, 349–374. https://doi.org/10.1146/annurev.ph.55.030193.002025

Slomine, B. S., Gerring, J. P., Grados, M. A., Vasa, R., Brady, K. D., Christensen, J. R., & Denckla, M. B. (2002). Performance on measures of “executive function” following pediatric traumatic brain injury. *Brain Injury*, *16*(9), 759–772. https://doi.org/10.1080/02699050210127286

Snellenberg, J. X. V., & Wager, T. D. (2009). Cognitive and Motivational Functions of the Human Prefrontal Cortex. In A.-L. Christensen, E. Goldberg, & D. Bougakov (Eds.), *Luria’s legacy in the 21st century* (pp. 30–61). Oxford University Press.

Snyder, H. R., Miyake, A., & Hankin, B. L. (2015). Advancing understanding of executive function impairments and psychopathology: bridging the gap between clinical and cognitive approaches. *Frontiers in Psychology*, *6*, 328. https://doi.org/10.3389/fpsyg.2015.00328

Staw, B. M. (1981). The Escalation of Commitment to a Course of Action. *The Academy of Management Review*, *6*(4), 577. https://doi.org/10.2307/257636

Stein, A. von, & Sarnthein, J. (2000). Different frequencies for different scales of cortical integration: from local gamma to long range alpha/theta synchronization. *International Journal of Psychophysiology*, *38*(3), 301–313. https://doi.org/10.1016/s0167-8760(00)00172-0

Stoet, G. (2010). PsyToolkit: A software package for programming psychological experiments using Linux. *Behavior Research Methods*, *42*(4), 1096–1104. https://doi.org/10.3758/brm.42.4.1096

Stoet, G. (2017). PsyToolkit. *Teaching of Psychology*, *44*(1), 24–31. https://doi.org/10.1177/0098628316677643

Stuss, D. T., & Alexander, M. P. (2000). Executive functions and the frontal lobes: a conceptual view. *Psychological Research*, *63*(3–4), 289–298. https://doi.org/10.1007/s004269900007

Swami, S. (2013). Executive functions and decision making: A managerial review. *IIMB Management Review*, *25*(4), 203–212. https://doi.org/10.1016/j.iimb.2013.07.005

Taasoobshirazi, G., & Farley, J. (2013). Construct Validation of the Physics Metacognition Inventory. *International Journal of Science Education*, *35*(3), 447–459. https://doi.org/10.1080/09500693.2012.750433

Tanaka, S. C., Samejima, K., Okada, G., Ueda, K., Okamoto, Y., Yamawaki, S., & Doya, K. (2006). Brain mechanism of reward prediction under predictable and unpredictable environmental dynamics. *Neural Networks*, *19*(8), 1233–1241. https://doi.org/10.1016/j.neunet.2006.05.039

Thoern, H. A., Grueschow, M., Ehlert, U., Ruff, C. C., & Kleim, B. (2016). Attentional Bias towards Positive Emotion Predicts Stress Resilience. *PLoS ONE*, *11*(3), e0148368. https://doi.org/10.1371/journal.pone.0148368

Thunholm, P. (2004). Decision-making style: habit, style or both? *Personality and Individual Differences*, *36*(4), 931–944. https://doi.org/10.1016/s0191-8869(03)00162-4

Tsukamoto, T., Kotani, Y., Ohgami, Y., Omura, K., Inoue, Y., & Aihara, Y. (2006). Activation of insular cortex and subcortical regions related to feedback stimuli in a time estimation task: An fMRI study. *Neuroscience Letters*, *399*(1–2), 39–44. https://doi.org/10.1016/j.neulet.2006.01.061

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Ullsperger, M., Fischer, A. G., Nigbur, R., & Endrass, T. (2014). Neural mechanisms and temporal dynamics of performance monitoring. *Trends in cognitive sciences*, *18*(5), 259-267. https://doi.org/10.1016/j.tics.2014.02.009

Ustárroz, J. T., Andrés, P. C., Lario, P. L., & Goñi, P. H. (2017). Propuesta de un modelo de funciones ejecutivas basado en análisis factoriales. *Revista de Neurología*, *64*(02), 75. https://doi.org/10.33588/rn.6402.2016227

van der Pligt, J. (2015). Decision Making, Psychology of. In *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)* (pp. 917–922). https://doi.org/10.1016/b978-0-08-097086-8.24014-2

Veenman, M. V. J. (2007). The assessment and instruction of self-regulation in computer-based environments: a discussion. *Metacognition and Learning*, *2*(2–3), 177–183. https://doi.org/10.1007/s11409-007-9017-6

Vijver, I. van de, Ridderinkhof, K. R., & Cohen, M. X. (2011). Frontal Oscillatory Dynamics Predict Feedback Learning and Action Adjustment. *Journal of Cognitive Neuroscience*, *23*(12), 4106–4121. https://doi.org/10.1162/jocn_a_00110

Völlm, B., Richardson, P., McKie, S., Elliott, R., Dolan, M., & Deakin, B. (2007). Neuronal correlates of reward and loss in Cluster B personality disorders: A functional magnetic resonance imaging study. *Psychiatry Research: Neuroimaging*, *156*(2), 151–167. https://doi.org/10.1016/j.pscychresns.2007.04.008

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

Ward, J. (2019). *The Student's Guide to Cognitive Neuroscience*. Routledge. https://doi.org/10.4324/9781351035187

Weatherly, N. L., & Malott, R. W. (2008). An Analysis of Organizational Behavior Management Research in Terms of the Three-Contingency Model of Performance Management. *Journal of Organizational Behavior Management*, *28*(4), 260–285. https://doi.org/10.1080/01608060802454643

Welsh, M. C., & Huizinga, M. (2001). The Development and Preliminary Validation of the Tower of Hanoi-Revised. *Assessment*, *8*(2), 167–176. https://doi.org/10.1177/107319110100800205

Whitebread, D., Coltman, P., Pasternak, D. P., Sangster, C., Grau, V., Bingham, S., Almeqdad, Q., & Demetriou, D. (2009). The development of two observational tools for assessing metacognition and self-regulated learning in young children. *Metacognition and Learning*, *4*(1), 63–85. https://doi.org/10.1007/s11409-008-9033-1

Wilson, M. (2002). Six views of embodied cognition. *Psychonomic Bulletin & Review*, *9*(4), 625–636. https://doi.org/10.3758/bf03196322

Winne, P. H., & Azevedo, R. (2014). Metacognition. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (2nd ed., pp. 66–87). Cambridge University Press.

Wofford, J. C., & Goodwin, V. L. (1990). Effects of Feedback on Cognitive Processing and Choice of Decision Style. *Journal of Applied Psychology*, *75*(6), 603–612. https://doi.org/10.1037/0021-9010.75.6.603

Woo, Y., Song, J., Jiang, Y., Cho, C., Bong, M., & Kim, S. (2015). Effects of informative and confirmatory feedback on brain activation during negative feedback processing. *Frontiers in Human Neuroscience*, *9*, 378. https://doi.org/10.3389/fnhum.2015.00378

Wróbel, A. (2000). Beta activity: a carrier for visual attention. *Acta Neurobiologiae Experimentalis*, *60*(2), 247–260. https://doi.org/10.55782/ane-2000-1344

Xi, W., Tian, M., & Zhang, H. (2011). Molecular imaging in neuroscience research with small-animal PET in rodents. *Neuroscience Research*, *70*(2), 133–143. https://doi.org/10.1016/j.neures.2010.12.017

Yen, H. R., & Chuang, S.-C. (2008). The effect of incidental affect on preference for the status quo. *Journal of the Academy of Marketing Science*, *36*(4), 522–537. https://doi.org/10.1007/s11747-008-0084-2

Yu, Y., Zhao, Y., Si, Y., Ren, Q., Ren, W., Jing, C., & Zhang, H. (2016). Estimation of the cool executive function using frontal electroencephalogram signals in first-episode schizophrenia patients. *BioMedical Engineering OnLine*, *15*(1), 131. https://doi.org/10.1186/s12938-016-0282-y

Zanto, T. P., Rubens, M. T., Thangavel, A., & Gazzaley, A. (2011). Causal role of the prefrontal cortex in top-down modulation of visual processing and working memory. *Nature Neuroscience*, *14*(5), 656–661. https://doi.org/10.1038/nn.2773

Zelazo, P. D. (2020). Executive Function and Psychopathology: A Neurodevelopmental Perspective. *Annual Review of Clinical Psychology*, *16*(1), 1–24. https://doi.org/10.1146/annurev-clinpsy-072319-024242

Zelazo, P. D., & Carlson, S. M. (2012). Hot and Cool Executive Function in Childhood and Adolescence: Development and Plasticity. *Child Development Perspectives*, *6*(4), 354–360. https://doi.org/10.1111/j.1750-8606.2012.00246.x

Zelazo, P. D., & Frye, D. (1998). Cognitive Complexity and Control. *Current Directions in Psychological Science*, *7*(4), 121–126. https://doi.org/10.1111/1467-8721.ep10774761

Zhang, L., & Cui, H. (2022). Reliability of MUSE 2 and Tobii Pro Nano at capturing mobile application users' real-time cognitive workload changes. *Frontiers in Neuroscience*, *16*, 1011475. https://doi.org/10.3389/fnins.2022.1011475

Personal publications

Balconi, M., Allegretta, R. A., & Angioletti, L. (2023). Autonomic synchrony induced by hyperscanning interoception during interpersonal synchronization tasks. *Frontiers in Human Neuroscience*, *17*, 1200750. https://doi.org/10.3389/fnhum.2023.1200750

Balconi, M., Acconito C., Allegretta, R. A. & Crivelli D. (2023). What Is the Relationship between Metacognition and Mental Effort in Executive Functions? The Contribution of Neurophysiology. *Behavioral Sciences*, *13*(11), 918. https://doi.org/10.3390/bs13110918

Crivelli, D., Allegretta, R. A., & Balconi, M. (2023). The "status quo bias" in Response to External Feedback in Decision-Makers. *Adaptive Human Behavior and Physiology*, *9*(4), 426-441. https://doi.org/10.1007/s40750-023-00230-1

Rovelli, K. & Allegretta, R. A. (2023). Framing decision-making: the role of executive functions, cognitive bias and reward. *Neuropsychological Trends*, *33*(1), 37-50. https://doi.org/10.7358/neur-2023-033-rove

Balconi, M., Acconito, B., Allegretta, R. A. & Angioletti, L. (2024). Neurophysiological and autonomic correlates of metacognitive control of and resistance to distractors in ecological setting. *Sensors, 24*(7), 2171. https://doi.org/10.3390/s24072171

Crivelli, D., Allegretta, R. A., & Balconi, M. (2024). Physiology of Risk-Taking and Risk Management in Realistic Decision-Making Scenarios. Psychological Reports, 0(0), 1-19. https://doi.org/10.1177/00332941241258919

Allegretta, R. A., Rovelli, K., & Balconi, M. (2024). The Role of Emotion Regulation and Awareness in Psychosocial Stress: An EEG-Psychometric Correlational Study. *Healthcare*, *12*(15), 1491. https://doi.org/10.3390/healthcare12151491

Balconi, M., Rovelli, K., Angioletti, L., & Allegretta, R. A. (2024). Working Memory Workload When Making Complex Decisions: A Behavioral and EEG Study. *Sensors*, *24*(17), 5754. https://doi.org/10.3390/s24175754

Balconi, M., Allegretta, R. A., Rovelli, K., & Acconito, C. (2024). Exploring self-relevance in decision-making: First-person, shared, or impersonal professional choice. Advances in Cognitive Psychology, 20(4), 376-388. https://doi.org/10.5709/acp-0440-5

Balconi, M., Angioletti, L., & Allegretta, R. A. (2025). Which Type of Feedback-Positive or Negative-Reinforces Decision Recall? An EEG study. *Frontiers in Systems Neuroscience*, *18*, 1524475. 10.3389/fnsys.2024.1524475

Balconi, M., Allegretta, R. A., & Angioletti, L. (2025). Metacognition of one's strategic planning in decision-making: the contribution of EEG correlates and individual differences. *Cognitive Neurodynamics*, *19*(1), 4. https://doi.org/10.1007/s11571-024-10189-8

Balconi, M., Allegretta, R. A., Acconito, C., Saquella, F., & Angioletti, L. (2025). The Functional Signature of Decision Making Across Dyads During a Persuasive Scenario: Hemodynamic fNIRS Coherence Measure. *Sensors*, 25(6), 1880. https://doi.org/10.3390/s25061880

Rovelli, K., Allegretta, R. A., & Balconi, M. (2025). Electroencephalographic and subjective profile in requesting and procrastinating: What it takes. *Journal of Neuroscience, Psychology, and Economics, 18*(1-2), 56–73. https://doi.org/10.1037/npe0000199

Balconi, M., Angioletti, L., & Allegretta, R. A. (2025). How to resist distraction in setting your goals: Neurophysiological and behavioral evidence. *Psychology & Neuroscience, 18*(3), 238–258. https://doi.org/10.1037/pne0000367

Allegretta, R. A., Rovelli, K., & Balconi, M. (2025). Converging Minds: EEG Synchrony During Communication About Moral Decision-Making in Dyadic Interactions. *Sensors*, *25*(13), 4239. https://doi.org/10.3390/s25134239

Allegretta, R.A., Angioletti, L., & Balconi, M. (2025). Analytic vs. Synthetic decision-making: A behavioral and EEG study with real-world decision-making scenarios. *Neurophysiology,* 1-10. https://doi.org/10.1007/s11062-025-09964-y

Balconi, M., Allegretta, R. A., Campanella, S., & Angioletti, L. (2025). Who can I rely on at work? EEG correlates and individual differences in the entrustment process. *Neuropsychological Trends, 38,* 57–81. https://doi.org/10.7358/neur-2025-038-balc

Allegretta, R. A., Daffinà, A., & Balconi, M. (2025). Frontal Delta Dissimilarity During Moral Persuasion: Insight from an EEG Hyperscanning Study. *Brain Sciences. 15*(12), 1302. https://doi.org/10.3390/brainsci15121302

Papers under review

Acconito, C., Allegretta, R.A., Angioletti, L., & Balconi, M. Ideal and real group representation in comparison: insights from a multimodal neurophysiological and autonomic hyperscanning study. *Brain Research*

Allegretta, R.A., & Balconi, M. Changing Mind or Holding Ground? Neural and Physiological Dynamics of Moral Persuasion. *Neuropsychologia*

Allegretta, R.A., Acconito, C., & Balconi, M. The influence of mental representation and individual differences on decision-making orientation. *Psychological Studies*

Allegretta, R.A., Angioletti, L., & Balconi, M. Get the spider out of the hole or see the hole? Analytic vs Synthetic strategic decision-making and decisional styles. *Current Psychology*

Allegretta, R.A., Ciminaghi, F., Angioletti, L., & Balconi, M. Does receiving positive or negative feedback change our memories about a decision we made? *Motivation & Emotion*

Allegretta, R.A., Daffinà, A., Balconi, M. Frontal delta dissimilarity during moral persuasion: insight from an EEG hyperscanning study. *Neuroscience Letters*

Allegretta, R.A., Rovelli, K., & Balconi, M. Follow morality for what reason and for what "value"? Personal choices and people's brains tell us. *The Social Science Journal*

Angioletti, L., Allegretta, R.A., & Balconi, M. EEG markers and self-perception process of moral negotiation during a persuasive interaction. *Adaptive Behavior*

Angioletti, L., Allegretta, R.A., & Balconi, M. Electrophysiology of Memorable Decisions: How positive, negative, and no feedback conditions influence decision retrieval. *Journal of Cognitive Psychology*

Balconi, M., Acconito, C., Angioletti, L., & Allegretta, R.A. Who can I rely on at work? EEG correlates and individual differences in the entrustment process. *Neuropsychological Trends*

Balconi, M., Allegretta, R. A., Acconito, C., & Rovelli, K. Single-subject and dyadic electroencephalography during persuasive communication: A hyperscanning paradigm applied to interpersonal synchronization. *Language, Cognition and Neuroscience*.

Balconi, M., Rovelli, K., & Allegretta, R.A. Brain and autonomic correlates of procrastination as "active" or "passive" strategy in decision-making. *Cognitive System Research*

Crivelli, D., Allegretta, R. A., Angioletti L., & Balconi, M. Assessing regulation and tolerance of acute psychosocial stress in professionals: is there an association between electrophysiological and behavioural markers? *International Journal of Selection and Assessment*

Allegretta, R. A., & Balconi M. Psychological and neurophysiological dissimilarity in moral reasoning: a correlational hyperscanning study. *Psychiatry International*

Conference contributions

Balconi, M., Di Lernia, D., Cassioli, F., Angioletti, L., De Gaspari, S., Serino, S., Sajno, E., Sansoni, M., Mauri, M., Rovelli, K., Allegretta, R. A., Amadini Genovese, L., & Riva, G. (2023, September 27–29). *Exploring the neurophysiological correlates of face-to-face vs. remote learning during lecture and group discussions: A hyperscanning paradigm* [Poster session]. 8th Scientific Meeting of the FESN & 2nd HNPS Conference, Thessaloniki, Greece.

Angioletti, L., Allegretta, R. A., & Balconi, M. (2023, September 27–29). *A biofeedback (BFB) study to investigate social interoception in dyads performing synchronization tasks* [Conference presentation]. 8th Scientific Meeting of the FESN & 2nd HNPS Conference, Thessaloniki, Greece.

Crivelli, D., Angioletti, L., Allegretta, R. A., & Balconi, M. (2023, June 21–23). *Screening of neurocognitive impairment in substance-use disorder and gambling disorder: Preliminary investigation on the role of age and clinical factors* [Conference presentation]. 58th AINPeNC Congress, Naples, Italy.

Crivelli, D., Allegretta, R. A., & Balconi, M. (2023, September 18–20). *Alterazioni neurocognitive nel disturbo da uso di sostanze e nel gioco d'azzardo patologico: Diversi profili di funzionamento?* [Conference presentation]. XXIX Congresso AIP – Sezione Sperimentale, Lucca, Italy.

Allegretta, R. A., Acconito, C., & Rovelli, K. (2023, September 18–20). *Autonomic measure responses to risk-taking and risk management in decision-making* [Conference presentation]. XXIX Congresso AIP – Sezione Sperimentale, Lucca, Italy.

Acconito, C., Allegretta, R. A., Crivelli, D., & Balconi, M. (2024, June 5–7). *How one's emotional and cognitive disposition influence moral decision making: The neuroscientific perspective* [Conference presentation]. Mind Matters – XV Meetings on Neuroscience and Society, Rome, Italy.

Allegretta, R. A., Rovelli, K., Angioletti, L., & Balconi, M. (2024, July 3–5). *The interplay of working memory and decisional complexity: Insights from behavioural and EEG measures* [Poster session]. INS Global Neuropsychology Congress, Oporto, Portugal.

Balconi, M., Allegretta, R. A., Angioletti, L., & Crivelli, D. (2024, July 3–5). *Assessing executive functions impairment in substance-related and behavioural addictions via the Battery for Executive Functions in Addiction (BFE-A): The role of age and clinical history* [Poster session]. INS Global Neuropsychology Congress, Oporto, Portugal.

Balconi, M., Allegretta, R. A., & Angioletti, L. (2024, July 3–5). *Examining metacognition in decision-making strategic planning: Insights from EEG correlates and individual differences* [Poster session]. INS Global Neuropsychology Congress, Oporto, Portugal.

Acconito, C., Angioletti, L., Allegretta, R. A., & Balconi, M. (2024, September 9–13). *Perceptual biases and individual differences during a visual decision-making task* [Poster session]. 9th International Conference on Spatial Cognition (ICSC 2024), Rome, Italy.

Allegretta, R. A., Angioletti, L., & Balconi, M. (2024, September 21–24). *Neurophysiological and behavioral evidence of distraction resistance in goal setting* [Poster session]. 37th ECNP Congress, Milan, Italy.

Acconito, C., Angioletti, L., Allegretta, R. A., & Balconi, M. (2024, September 21–24). *Cortical networks of representation in decision-making of group-individual and ideal-real condition* [Poster session]. 37th ECNP Congress, Milan, Italy.

Angioletti, L., Allegretta, R. A., & Balconi, M. (2024, September 21–24). *A neurocognitive protocol for assessing and empowering executive functions in behavioral addiction* [Poster session]. 37th ECNP Congress, Milan, Italy.

Allegretta, R. A., Angioletti, L., & Balconi, M. (2024, September 23–25). *Resisting distraction during goal setting: Insight from neurophysiological and behavioral data* [Poster session]. XXX Congresso Nazionale AIP, Noto (SR), Italy.

Acconito, C., Angioletti, L., Allegretta, R. A., & Balconi, M. (2024, September 23–25). *Ideal and mental representation in individual or group-oriented people: A neuroscientific perspective* [Poster session]. XXX Congresso Nazionale AIP, Noto (SR), Italy.

Allegretta, R. A., Rovelli, K., Angioletti, L., & Balconi, M. (2024, December 13). *Strategie di regolazione emotiva e feedback sociale: Un'analisi EEG delle performance cognitive sotto stress moderato* [Poster session]. Riunione Autunnale SINP, Bologna, Italy.

Angioletti, L., Allegretta, R. A., Daffinà, A., & Balconi, M. (2024, December 13). *Nuove prospettive per la valutazione neurocognitiva delle dipendenze comportamentali: Uno studio mediante BFE-A* [Poster session]. Riunione Autunnale SINP, Bologna, Italy.

Ciminaghi, F., Allegretta, R. A., Rovelli, K., & Balconi, M. (2024, December 13). *Effetti del feedback positivo e negativo sulla memoria decisionale e sull'attivazione neurale: Un'analisi comportamentale ed elettroencefalografica in decisori junior e senior* [Poster session]. Riunione Autunnale SINP, Bologna, Italy.

Balconi, M., Angioletti, L., Acconito, C., Rovelli, K., Crivelli, D., & Allegretta, R. A. (2025, May 16–17). *Neurofisiologia del decision-making: Consapevolezza della scelta e ruolo del feedback* [Poster session]. Congresso Nazionale SINP, Urbino, Italy.

Allegretta, R. A., Rovelli, K., Angioletti, L., Daffinà, A., Ciminaghi, F., & Balconi, M. (2025, May 30). *Dinamiche neurocognitive del giudizio morale e dell'etica aziendale: Un confronto tra professionisti junior e senior* [Poster session]. XVIII Convegno Nazionale S.I.P.I., Padova, Italy.

Allegretta, R. A., Ciminaghi, F., Angioletti, L., Rovelli, K., & Balconi, M. (2025, May 30). *Bias, valenza del feedback e fattore età nel ricordo delle proprie decisioni* [Poster session]. XVIII Convegno Nazionale S.I.P.I., Padova, Italy.

Allegretta, R. A., Angioletti, L., Rovelli, K., Ciminaghi, F., Daffinà, A., & Balconi, M. (2025, September 11-13). *Comparing ideal and real group mental representations: a multimodal* *hyperscanning study* [Conference presentation]. XXXI Congresso AIP – Sezione Sperimentale, Turin, Italy.

Allegretta, R. A., Angioletti, L., & Balconi, M. (2025, September 23-26). *Ideal vs. real group mental representation: insights from EEG-fNIRS-BIO multimodal hyperscanning study* [Poster session]. Society for Social Neuroscience S4SN 2025 – Lisbon, Portugal.

Daffinà, A., Allegretta, R. A., & Balconi, M. (2025, September 23-26). *Dyadic brain dynamics in moral persuasion: the role of frontal delta dissimilarity* [Poster session]. Society for Social Neuroscience S4SN 2025 – Lisbon, Portugal.

Allegretta, R. A., Angioletti, L., & Balconi, M. (2025, November 13-14). *Neurofisiologia del ragionamento morale: un confronto tra prospettiva in prima e terza persona* [Conference presentation]. Conferenza di Midterm SINe-APS "Sfide neurotecnologiche: tra etica e diritto" – Milan, Italy

La borsa di dottorato è stata cofinanziata con risorse del Piano Nazionale di Ripresa e Resilienza PNRR Componente 1 “Potenziamento dell’offerta dei servizi di istruzione: dagli asili nido all’Università” - Componente 2 “Dalla Ricerca all'Impresa”, Investimento 3.3, Introduzione di dottorati innovativi che rispondono ai fabbisogni di innovazione delle imprese e promuovono l'assunzione dei ricercatori da parte delle imprese”

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