

DOCTORAL (PhD) DISSERTATION

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**Neurocognitive mechanisms across the spectrum of
obsessive-compulsive tendencies:
the role of statistical learning**

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**Neurocognitive mechanisms across the spectrum of obsessive-
compulsive tendencies: the role of statistical learning**

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a doktori értekezés szerzőjének aláírása

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List of Abbreviations

ADHD	=	Attention Deficit Hyperactivity Disorder
AGL	=	Artificial Grammar Learning
ASD	=	Autism Spectrum Disorder
ASRT	=	Alternating Serial Reaction Time
CBT	=	Cognitive Behavioural Therapy
CI	=	Confidence Interval
CST	=	Card Sorting Task
DSM	=	Diagnostic and Statistical Manual of Mental Disorders
EEG	=	Electroencephalography
EF	=	Executive Functions
ERP	=	Exposure and Response Prevention
HiTOP	=	Hierarchical Taxonomy of Psychopathology
ICD	=	International Classification of Diseases
LMM	=	Linear Mixed Model
N	=	Sample size
M	=	Mean
OCD	=	Obsessive-Compulsive Disorder
OC	=	Obsessive-Compulsive
OCI-R	=	Obsessive-Compulsive Inventory-Revised
OCI-12	=	12-item version of the Obsessive-Compulsive Inventory-Revised
RDoC	=	Research Domain Criteria
RT	=	Reaction Time
SD	=	Standard Deviation
SE	=	Standard Error
SEM	=	Standard Error of the Mean
SL	=	Statistical Learning
SRT	=	Serial Reaction Time
SSRI	=	Selective Serotonin Reuptake Inhibitor
WPT	=	Weather Prediction Task

1. General introduction

Obsessive-Compulsive Disorder (OCD) is a chronic psychiatric condition characterized by persistent and intrusive thoughts, urges, or images, accompanied by repetitive and rigid behavioral or mental acts performed to alleviate distress or prevent anticipated harm (American Psychiatric Association, 2022). Its lifetime prevalence in the adult population is estimated to be approximately 2-3% (Karno et al., 1988; Stein et al., 2025). The etiology of OCD is multifactorial, arising from complex interactions among genetic susceptibility (Mahjani et al., 2021; Monzani et al., 2014; Pauls, 2010; Strom et al., 2021), environmental influences (Brander et al., 2016; Monzani et al., 2014; Raposo-Lima & Morgado, 2020), and neurobiological alterations (Ahmari & Rauch, 2022; Boedhoe et al., 2017; Burguière et al., 2015; Graybiel & Rauch, 2000; Tao et al., 2023; Thorsen et al., 2026; Van den Heuvel et al., 2022; Zarei et al., 2011). Within this integrative framework, research has increasingly focused on the neurobiological mechanisms underlying OCD, particularly structural and functional abnormalities in frontostriatal circuitry (Diwadkar et al., 2015; Graybiel & Rauch, 2000; Hou et al., 2014; Naze et al., 2023; Rosenberg et al., 1997; Ziegler et al., 2019) with alterations reported in the prefrontal cortex (Ahmari & Rauch, 2022; Thorsen et al., 2026; Vaghi et al., 2017), orbitofrontal cortex (Chamberlain et al., 2008; Harrison et al., 2013), striatum (Ahmari et al., 2013; Burguière et al., 2015; J. S. Choi et al., 2007; Diwadkar et al., 2015; Marsh et al., 2014; Tang et al., 2016; Zhang et al., 2019), thalamus (Li et al., 2019; Tang et al., 2016; Zhang et al., 2019), cerebellum (Narayanaswamy et al., 2016; Shobeiri et al., 2023; Xu et al., 2019; Zhang et al., 2019), and the anterior cingulate cortex (Diwadkar et al., 2015; Fitzgerald et al., 2005; Kühn et al., 2013; Szeszko et al., 2004). Many of the neural systems implicated in OCD support cognitive functions involved in learning, memory, and behavioral control, which has motivated growing interest in how alterations in these processes may contribute to obsessive-compulsive (OC) symptoms.

Accordingly, cognitive neuroscience models of OCD have increasingly focused on alterations in learning and behavioral control as potential mechanisms underlying the development and maintenance of core OCD symptoms (Ahmari & Rauch, 2022; Gillan, Apergis-Schoute, et al., 2015; Gillan et al., 2011, 2014; Graybiel & Rauch, 2000; Hansmeier et al., 2018; Kathmann et al., 2005). Many of these models emphasize a dysregulation between goal-directed and habitual control systems, suggesting that compulsive behavior arises from an imbalance characterized by impaired goal-directed control and a relative overreliance on habitual responding (Banca et al., 2024; Gillan et al., 2011; Gillan & Robbins, 2014; Yu et al., 2024). Complementary lines of research have implicated implicit learning and memory processes in OCD symptomatology (Deckersbach et al., 2002; Exner et al., 2014; Goldman et al., 2008; Graybiel & Rauch, 2000; Hansmeier et al., 2018; Kathmann et al., 2005; Kelmendi et al., 2016; Marker et al., 2006; Soref et al., 2018, 2021; Vloet et al., 2010; Zetsche et al., 2015). While these models have substantially advanced our understanding of OCD, the disorder is unlikely to be explained by a single neurocognitive mechanism, given its considerable heterogeneity in both symptom presentation and neurocognitive functioning. Importantly, variability in OC symptoms and related cognitive characteristics extends beyond diagnostic boundaries, supporting their conceptualization along a continuum.

Capturing this variability requires moving beyond categorical diagnostic boundaries and considering individual differences across the broader OC continuum. Accordingly, the present dissertation adopts a dimensional, spectrum-based perspective, encompassing the full range of OC characteristics from mild, subclinical tendencies to severe, clinically impairing manifestations (Fullana et al., 2010; Mataix-Cols et al., 2005). Within this framework, OC tendencies refer to dimensional variations in intrusive

thoughts and compulsive behaviors that vary continuously across individuals (Fullana et al., 2010; Mataix-Cols et al., 2005; Rachman & de Silva, 1978). The empirical studies of the present dissertation focus on individual variation in these tendencies within non-clinical populations, while considering their relevance to the broader OC spectrum and to clinical OCD. The theoretical and methodological basis of this perspective, including its relationship to contemporary dimensional and transdiagnostic frameworks, is discussed in detail in Section 1.2.

Building on this clinical and conceptual background, the following sections outline the key neurocognitive frameworks that guide the present dissertation. In particular, this dissertation examines learning from two complementary perspectives. The first focuses on **supervised learning**, broadly referring here to learning guided by external information, such as feedback, reinforcement, or action outcomes (Gillan et al., 2011; Gillan & Robbins, 2014; Zhong et al., 2025). The second addresses **unsupervised learning**, referring to the acquisition of environmental regularities without explicit feedback or reinforcement concerning the underlying structure (Aslin, 2017; Conway, 2020; Zhong et al., 2025). By considering these complementary forms of learning, the dissertation aims to clarify how different learning processes relate to individual differences in OC tendencies. In addition to these learning processes, adaptive behavior depends on executive functions (EF) that support flexible and goal-directed behavioral control. Together, these processes provide a broader framework for understanding the balance between automatic and goal-directed behavior in relation to OC tendencies.

1.1. Obsessive-Compulsive Disorder: Clinical characteristics

The conceptualization of OCD has changed considerably over the past two centuries. Early accounts often interpreted obsessive thoughts and repetitive behaviors in religious or moral terms, whereas nineteenth-century psychiatry increasingly regarded them as symptoms of a mental disorder (Alvarenga et al., 2007). During the first half of the twentieth century, psychoanalytic theories explained obsessions and compulsions in terms of unconscious conflicts, with compulsive rituals viewed as attempts to reduce the resulting anxiety (Kempke & Luyten, 2007; Salkovskis, 1999). Behavioral and cognitive theories later shifted the focus toward learning processes, proposing that compulsions may persist because they temporarily reduce the distress associated with obsessive thoughts and are therefore negatively reinforced (Salkovskis, 1999).

The diagnostic classification of OCD has undergone a similar conceptual evolution. Early classification systems, including the sixth edition of the International Classification of Diseases (ICD, World Health Organization, 1948) and the first edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-I; American Psychiatric Association, 1952), classified OCD within a broader psychoneurotic framework. A major shift occurred with DSM-III (American Psychiatric Association, 1980), which moved away from psychoanalytic etiological assumptions toward operationalized, symptom-based diagnostic criteria and classified OCD among the anxiety disorders. Accumulating evidence from genetic, neuropsychological, and neuroimaging research subsequently suggested important differences between OCD and other anxiety disorders, contributing to a reconsideration of its diagnostic placement (Phillips et al., 2010; Stein et al., 2010). Reflecting this shift, DSM-5 (American Psychiatric Association, 2013) and ICD-11 (World Health Organization, 2024) placed OCD within separate groupings of obsessive-compulsive and related disorders. Clinically, OCD is characterized by obsessions, compulsions, or their co-occurrence (American Psychiatric Association, 2022; American Psychiatric Association, 2013). Obsessions may involve diverse themes, including

contamination, responsibility for harm, symmetry, or unacceptable intrusive thoughts, whereas compulsions may include overt behaviors such as washing, checking, and ordering, as well as covert mental rituals. These symptoms can vary considerably in their content and severity and may interfere with everyday functioning to different degrees (American Psychiatric Association, 2013, 2022). The current DSM-5-TR diagnostic criteria for OCD are summarized in Table 1.

Table 1

Overview of the DSM-5-TR Diagnostic Criteria for Obsessive-Compulsive Disorder

Criterion	Diagnostic requirement	Brief description
A	Presence of obsessions, compulsions, or both	Obsessions involve recurrent, intrusive thoughts, urges, or images associated with distress; compulsions involve repetitive behaviors or mental acts typically performed to reduce distress or prevent feared outcomes.
B	Clinical significance	Symptoms are time-consuming (>1 hour per day) or cause clinically significant distress or impairment in important areas of functioning.
C	Exclusion of substance or medical causes	The symptoms are not attributable to the physiological effects of a substance, medication, or another medical condition.
D	Differential diagnosis	The symptoms are not better explained by another mental disorder, such as generalized anxiety disorder, body dysmorphic disorder, hoarding disorder, eating disorders, or psychotic disorders.
Specifiers	Insight and tic-related status	Insight is specified as good/fair, poor, or absent/delusional. OCD may additionally be specified as tic-related when there is a current or past history of a tic disorder.

Note. Adapted and summarized from the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, Text Revision* (DSM-5-TR; American Psychiatric Association, 2022).

1.1.1. Treatment of OCD

Current clinical guidelines recommend cognitive-behavioral therapy (CBT), particularly exposure and response prevention (ERP), and selective serotonin reuptake inhibitors (SSRIs) as first-line treatments for OCD (Abramowitz, 2006; Bandelow et al., 2023; Fineberg et al., 2020; Fineberg & Gale, 2005). Both psychological and pharmacological interventions have demonstrated efficacy, although treatment should be individualized according to the clinical presentation (Fineberg et al., 2020; Pittenger et al., 2021). Relevant considerations include predominant OCD symptom dimensions and overall symptom severity, comorbid anxiety and depressive symptoms, suicidality, previous treatment response, patient preferences, and available therapeutic resources

(Abramowitz, 2006; Bandelow et al., 2023; Fineberg et al., 2020; Fineberg & Gale, 2005). In more severe or clinically complex presentations, or following an inadequate response to monotherapy, combined psychological and pharmacological treatment may be considered (Abramowitz, 2006; Bandelow et al., 2023; Fineberg et al., 2020; Fineberg & Gale, 2005).

ERP is particularly relevant from a neurocognitive perspective because it is fundamentally learning-based (Öst et al., 2015). During exposure, patients systematically confront stimuli, thoughts, or situations that evoke obsessive concerns and associated distress, while response prevention involves refraining from the compulsive rituals or avoidance behaviors that would ordinarily follow (Abramowitz, 2006; Öst et al., 2015; Skapinakis et al., 2016). Repeated exposure in the absence of the compulsive response provides opportunities to experience distress without relying on rituals and to revise expectations concerning anticipated negative outcomes. Importantly, ERP is tailored to the predominant symptom presentation rather than being implemented uniformly across patients (Abramowitz, 2006; Fineberg et al., 2020). Traditionally, the therapeutic effects of ERP were primarily explained in terms of habituation, whereby repeated exposure was expected to produce a gradual reduction in anxiety. Contemporary accounts increasingly emphasize inhibitory learning, according to which exposure facilitates new learning that competes with existing threat-related associations rather than simply eliminating them (Craske et al., 2014).

Pharmacological treatment primarily relies on SSRIs, which represent the first-line pharmacological option for OCD (Bandelow et al., 2023; Fineberg et al., 2015; Fineberg & Gale, 2005; Pittenger et al., 2021; Skapinakis et al., 2016). Following insufficient response to first-line treatment, strategies may include combining psychotherapy and pharmacotherapy, optimizing or switching medication, or considering augmentation approaches (Bandelow et al., 2023; Pittenger et al., 2021). Despite the established efficacy of first-line interventions, treatment response remains heterogeneous, and a considerable proportion of patients experience only partial improvement or persistent residual symptoms (Abramowitz, 2006; Fineberg et al., 2020). This variability underscores the importance of identifying cognitive and neurobiological mechanisms that may contribute to individual differences in treatment response.

1.2. From categorical diagnosis to dimensional conceptualizations of OCD

The considerable heterogeneity of psychopathology has challenged the assumption that psychiatric disorders form clearly defined and discrete diagnostic categories (Krueger et al., 2018). Although the DSM and ICD have improved the standardization and reliability of psychiatric diagnosis, categorical classification captures only part of the complexity of psychopathology (Kotov et al., 2017, 2021). Psychiatric disorders frequently share genetic, neurobiological, and cognitive mechanisms and show high rates of comorbidity, further questioning clear boundaries between diagnostic categories (Abramovitch et al., 2021; Bourque et al., 2024; Grotzinger, 2021). Moreover, psychopathological symptoms may extend beyond diagnostic boundaries and occur below the threshold for a specific diagnosis (Buchweitz et al., 2026; Mataix-Cols et al., 2005). Collectively, these observations challenge a strictly binary distinction between mental health and disorder and highlight the loss of clinically relevant information inherent in exclusively categorical classification.

These limitations have led to increasing interest in dimensional approaches, which conceptualize psychopathology as varying along a continuum rather than exclusively as discrete categories. Two influential frameworks that have contributed to moving beyond

traditional diagnostic categories are the Research Domain Criteria (RDoC, Cuthbert & Insel, 2013; Insel et al., 2010; Insel, 2014) and the Hierarchical Taxonomy of Psychopathology (HiTOP, Kotov et al., 2017, 2021, 2022). RDoC provides a mechanistically oriented research framework that investigates neurobehavioral constructs, including cognitive control, reward processing, threat responsiveness, and arousal, across multiple levels of analysis and across the full range of functioning, rather than within conventional diagnostic categories (Cuthbert & Insel, 2013; Insel, 2014; Insel et al., 2010). In contrast, HiTOP empirically organizes covarying psychopathological symptoms and traits into a dimensional hierarchy ranging from specific symptom components and syndromes to broader psychopathological spectra (Kotov et al., 2017, 2021, 2022). Thus, the two frameworks provide complementary perspectives beyond categorical nosology: RDoC primarily emphasizes mechanisms underlying psychopathology, whereas HiTOP addresses its empirical dimensional organization.

Within a dimensional approach, a spectrum perspective considers related psychopathological characteristics across their full range of severity, including both clinical and non-clinical levels (Fullana et al., 2010; Mataix-Cols et al., 2005). From this perspective, clinical and non-clinical manifestations are considered along a continuum and may differ in their severity, persistence, associated distress, and functional impairment (Abramowitz et al., 2014; Fullana et al., 2010; Mataix-Cols et al., 2005; Rachman & de Silva, 1978). The term non-clinical refers to characteristics or symptoms that are present below the threshold for a clinical diagnosis and do not necessarily involve the severity, distress, or functional impairment required for a diagnosed disorder (Abramowitz et al., 2014; Rachman & de Silva, 1978). In the context of OCD, the present dissertation uses the term OC tendencies to refer to dimensional variation in obsessive and compulsive characteristics, particularly at the non-clinical level examined in the empirical studies. A spectrum perspective therefore does not eliminate the clinical relevance of diagnostic thresholds but recognizes variation beyond these boundaries.

Evidence for a continuum of OC phenomena has a long history in OCD research. Rachman and de Silva (1978) showed that intrusive thoughts resembling clinical obsessions are also common in the general population, with clinical and non-clinical experiences differing in characteristics such as frequency, intensity, and associated distress. Subsequent research extended this dimensional perspective beyond intrusive thoughts, providing further support for continuous variation in OC symptoms across clinical and non-clinical populations (Abramowitz et al., 2014; Fullana et al., 2010). At the same time, OCD is itself multidimensional: partially distinct symptom dimensions, including contamination/cleaning, responsibility for harm/checking, symmetry/ordering, and unacceptable thoughts, may vary relatively independently across individuals (Mataix-Cols et al., 2005). Thus, dimensionality in OCD can be considered at two levels: variation in the overall degree of OC symptoms across individuals and variation in the relative prominence of different symptom dimensions. This conceptualization has important methodological implications. If OC symptoms extend continuously beyond the diagnostic threshold, individual variation in OC tendencies within the general population provides a valuable analogue sample for investigating cognitive and neurocognitive processes relevant to OCD (Abramowitz et al., 2014). Such an approach allows OC-related neurocognitive variation to be examined across levels of symptom severity without relying exclusively on diagnostic group comparisons.

Building on these conceptual advances, the present dissertation adopts a spectrum-based approach to OCD, conceptualizing OC tendencies as continuously varying characteristics rather than phenomena confined to a diagnostic category. Accordingly, Studies 2 and 3 examine individual variability in OC tendencies within the

general population and its neurocognitive correlates, with particular emphasis on learning and EFs. Thus, rather than treating diagnostic status as the primary unit of analysis, the present work examines how neurocognitive functioning varies across levels of OC tendencies.

1.3. Supervised learning

Supervised learning refers broadly to learning in which behavior is shaped by external information, such as feedback, reinforcement, or reward (Gillan et al., 2011; Zhong et al., 2025). In OCD research, supervised paradigms have been particularly influential in examining the balance between goal-directed and habitual control and the acquisition of probabilistic cue-outcome relationships (Exner et al., 2014; Gillan et al., 2011; Hansmeier et al., 2018).

1.3.1. Habit hypothesis in OCD

Efficient adaptive functioning in everyday life relies on the coordinated balance of habitual and goal-directed behavior, enabling individuals to act efficiently while remaining flexible in response to changing environmental demands (Balleine & O'Doherty, 2010). Goal-directed behavior is supported by executive functions (EF), a set of higher-order, complex cognitive functions that orchestrate attention, flexibility, inhibition, and working memory, enabling the flexible implementation of behavior in accordance with current goals (Diamond, 2013; Friedman & Robbins, 2022; Miyake et al., 2000). Together, these functions support the maintenance and updating of goal representations, the inhibition of inappropriate responses, and the coordination of complex actions, thereby enabling goal attainment while avoiding adverse outcomes (Friedman & Robbins, 2022). In contrast, habitual behavior traditionally emerges through repeated reinforcement and gradually becomes insensitive to outcome value (Anthony Dickinson, 1985; Balleine & O'Doherty, 2010; Carden & Wood, 2018; Gillan, Otto, et al., 2015). More broadly, habitual actions rely predominantly on previously acquired stimulus-response associations and require less deliberative control than goal-directed actions (Ashby et al., 2010; Carden & Wood, 2018; Horváth et al., 2022; Kaufman et al., 2010). In OCD, compulsive responses may be reinforced by the temporary relief they provide from obsession-related distress, contributing to their repetition and persistence (American Psychiatric Association, 2022; Salkovskis, 1999). Crucially, this maladaptive habitual control emerges when the habitual system dominates over goal-directed behavior or goal-directed behavior is disrupted (Anthony Dickinson, 1985). The habit hypothesis of OCD therefore proposes that compulsive behavior arises from an imbalance between these systems, characterized by impaired goal-directed control and a relative overreliance on habitual responding (Gillan, Apergis-Schoute, et al., 2015; Gillan et al., 2011, 2014, 2020; Robbins et al., 2019).

Empirical support for this hypothesis comes from studies using mostly outcome devaluation paradigms and contingency degradation (Gillan, 2021; Gillan et al., 2011, 2014; Robbins et al., 2019; Vaghi et al., 2019). In outcome devaluation tasks, continued responding despite a reduction in outcome value indicates habitual control, whereas contingency-degradation paradigms weaken the relationship between an action and its outcome (Robbins et al., 2019). Goal-directed behavior is expected to adjust to these changes, whereas continued responding despite changes in outcome value or action-outcome contingency indicates greater reliance on habitual control (Gillan, 2021; Gillan et al., 2011, 2014). A key question, however, is whether this insensitivity to devaluation arises from an excessive accumulation of habitual responses or impaired goal-directed,

action-outcome control (Donegan et al., 2025). According to findings from decision-making tasks and computational modeling, the habit bias observed in OCD appears to be driven more by impairments in goal-directed control than by heightened habit formation (de Wit et al., 2018; Gillan et al., 2014; Voon et al., 2015). Importantly, reduced goal-directed control has also been associated with compulsivity beyond clinically diagnosed OCD, suggesting that this imbalance may vary dimensionally with compulsive tendencies rather than being specific to OCD diagnosis (Gillan et al., 2020), highlighting the importance of examining the neurocognitive mechanisms underlying compulsive behavior both clinically and across subclinical symptom dimensions.

1.3.2. Probabilistic classification approach

Another supervised approach used to investigate learning in OCD is probabilistic classification learning, commonly assessed with the Weather Prediction Task (WPT; Knowlton et al., 1994). In this task, participants gradually learn probabilistic cue-outcome associations through trial-by-trial feedback and use them to predict one of two possible outcomes (Knowlton et al., 1994). Studies using neutral stimuli have generally found WPT performance to be intact in individuals with OCD relative to healthy controls (Exner et al., 2014; Hansmeier et al., 2018; Zetsche et al., 2015), with only selective impairments observed in specific subgroups (Kelmendi et al., 2016). Differences have been reported when probabilistic learning involves symptom-relevant or emotionally salient information. For example, modified versions of the WPT employing threat-related stimuli, predicting the outbreak of an epidemic from viral cues, have revealed impaired performance in OCD (Exner et al., 2014; Hansmeier et al., 2018; Zetsche et al., 2015). Together, these findings do not support a generalized impairment in probabilistic classification learning in OCD but suggest that performance may be influenced by the emotional or symptom relevance of the learned information (Exner et al., 2014; Hansmeier et al., 2018; Kelmendi et al., 2016; Zetsche et al., 2015).

This section reviewed supervised learning mechanisms in OCD, focusing on the habit hypothesis and probabilistic classification paradigms. Although these approaches often report intact learning performance at the behavioral level (Exner et al., 2014; Hansmeier et al., 2018; Zetsche et al., 2015), they capture only a limited subset of the complex neurocognitive processes implicated in OCD. Because performance in supervised tasks depends on external feedback or reinforcement, it reflects both the acquisition of associations and the processing of their outcomes. This distinction may be particularly relevant in OCD given evidence for altered reward and reinforcement processing (Alves-Pinto et al., 2019; Figeo et al., 2011; Kaufmann et al., 2013). Consequently, supervised paradigms offer only limited insight into the underlying pure learning mechanisms, as task performance is heavily shaped by external feedback. This distinction may be particularly relevant in OCD, as reinforcement-learning studies have identified alterations in reward- and outcome-related processing, including differences in learning from specific prediction errors and in the neural processing of reinforcement outcomes (Marsh et al., 2015; Suzuki et al., 2023; Voon et al., 2015). Thus, behavioral differences observed in supervised learning paradigms cannot necessarily be attributed to associative learning itself, as they may also reflect variation in feedback, reward, or outcome processing. Explicit signals indicating correct and incorrect responses further confound learning processes with outcome evaluation, making it difficult to determine whether observed behavioral patterns genuinely reflect learning mechanisms or are predominantly driven by secondary effects related to reward processing and feedback sensitivity. In addition,

supervised paradigms can fail to decompose behavior into its constituent cognitive components at a sufficiently fine-grained, process-specific level. This limitation has drawn increasing methodological attention, particularly regarding their capacity to capture habit expression accurately (de Wit et al., 2018; Donegan et al., 2025; Gera et al., 2023). Heightened habit performance observed in these tasks is difficult to interpret, as it may reflect diminished goal-directed control, exaggerated stimulus–response associations, or a combination of both (Donegan et al., 2025). Together, these considerations underscore the need for alternative approaches capable of isolating pure learning mechanisms and reliably measuring habitual behavior.

1.4. Unsupervised learning

Unsupervised learning occurs in the absence of explicit instruction, feedback, or reinforcement and allows regularities to be acquired directly from environmental input (Aslin, 2017; Castro et al., 2018; Conway, 2020; Love, 2002; Zhong et al., 2025). A recent neurobiological study conceptualizes unsupervised learning as a primary mechanism that underpins more complex, supervised learning processes, and empirically demonstrates that a substantial portion of neural plasticity in the visual cortex emerges through unsupervised exposure to sensory input, independent of explicit reward or task-related feedback (Zhong et al., 2025). Neural changes induced by such unsupervised learning largely overlap with those observed during reward-based, task-driven learning, suggesting that the brain inherently acquires the statistical structure of the environment prior to reinforcement (Zhong et al., 2025). Importantly, unsupervised pretraining facilitates subsequent supervised learning, indicating that feedback-based mechanisms operate on representations already shaped by reward-independent processes (Zhong et al., 2025). Hence, these findings challenge purely supervised accounts of learning and suggest that learning dysfunctions may require examination at the level of primary, unsupervised mechanisms.

Unsupervised learning has been proposed as a fundamental mechanism underlying the acquisition of skills, habits, and automatic behaviors (Conway, 2020; Horváth et al., 2022; Kaufman et al., 2010). Critically, habitual behavior can develop entirely implicitly through repeated exposure and practice, independent of reward/feedback or conscious guidance, with statistical learning (SL) serving as a central process in this formation (Horváth et al., 2022; Kaufman et al., 2010). SL, the extraction of regularities and deterministic or probabilistic structures from the environment, provides a mechanism by which environmental patterns are encoded and subsequently expressed as automatic and habit-like behaviors (Conway, 2020; Fiser & Aslin, 2005; Pedraza et al., 2024; Theeuwes et al., 2022). This provides a framework for examining learning processes that operate outside classical reinforcement-based paradigms (Foerde, 2018; Horváth et al., 2022; Seger & Miller, 2010). Empirical investigations of unsupervised learning mechanisms have commonly relied on visuomotor learning paradigms, particularly the Serial Reaction Time (SRT) task (Nissen & Bullemer, 1987). In this task, participants respond to sequential stimuli by pressing keys corresponding to stimulus locations, while remaining unaware that the sequence of stimulus locations follows a hidden regularity. In the classical SRT task, stimulus transitions are usually fully deterministic: each stimulus is completely predictable with a transitional probability of one (Deroost & Soetens, 2006; Du & Kelly, 2013; Nissen & Bullemer, 1987; Remillard, 2003, 2014). This means that these tasks measure simple, first- or second-order adjacent regularities (Remillard, 2003). Learning is inferred from progressively faster reaction times (RT) across training and a marked increase in RT when the sequence

is unexpectedly altered (Nissen & Bullemer, 1987). The SRT task engages a mechanism that relies on the acquisition of sequential regularities, which is commonly known as sequence learning or deterministic learning in the literature. In this dissertation, I will use the term 'deterministic learning' consistently when discussing the classical SRT task.

Within the context of OCD, investigating unsupervised learning is particularly important, as the neurobiological substrates engaged by the SRT task (Janacsek et al., 2020) including striatal regions, such as the putamen, are also implicated in the disorder (Ahmari et al., 2013; Burguière et al., 2015; Graybiel & Rauch, 2000; Zhang et al., 2019). Studies employing deterministic SRT paradigms have generally reported impaired or reduced performance in OCD (Deckersbach et al., 2002; Goldman et al., 2008; Kathmann et al., 2005; Marker et al., 2006; Sorel et al., 2018; Vloet et al., 2010, for exceptions, see: Rauch et al., 1997, 2007), leading to the interpretation of a potential deficit in deterministic learning. In Study 1, we sought to present a brief, focused review of unsupervised learning processes in OCD, focusing on evidence from classical deterministic SRT paradigms. Specifically, this study adopted a process-level perspective to disentangle the multiple cognitive and behavioral processes captured by the SRT task. Sequence-specific learning (i.e., learning the sequential order of elements), visuomotor performance (i.e., improvements in RT due to motor practice), and general (baseline) RT performance were examined separately, along with their associated neurocognitive correlates (Janacsek et al., 2020). This approach allows for a more nuanced interpretation of prior findings and clarifies which components of task performance may be altered in individuals with OCD.

1.5. Challenges in OCD research

1.5.1. Theoretical challenges

Although deterministic learning provides a useful model of unsupervised learning, its fixed structure primarily captures the acquisition of predictable sequences and may therefore only partially reflect learning in variable, noisy environments. In real-life contexts, regularities, correlations, and patterns are acquired incidentally and implicitly, often amid noise, through probabilistic learning. Probabilistic learning captures this process more generally, supporting the extraction of environmental regularities and the anticipation of future events (Aslin, 2017; Fiser & Aslin, 2005; Pedraza et al., 2024; Theeuwes et al., 2022). Throughout this dissertation, 'deterministic learning' refers to learning based on fully predictable sequences (e.g., classic SRT tasks), whereas 'probabilistic learning' or 'statistical learning (SL)' interchangeably refers to the extraction of regularities from probabilistic, less predictable environments.

Despite its fundamental role, unsupervised probabilistic learning remains largely unexplored in OCD. This is particularly relevant because SL supports the acquisition of linguistic, motor, cognitive, and habitual behaviors that rely on extracting probabilistic regularities from the environment (Arciuli, 2018; Bogaerts et al., 2021; Horváth et al., 2022; Kaufman et al., 2010; Pesthy et al., 2024; Ullman, 2004). Examining SL in OCD may therefore provide a more ecologically relevant model of how regularities are acquired from noisy and variable environments.

1.5.2. Methodological challenges

From a methodological perspective, although the classical SRT task reduces the influence of confounding reward and feedback effects compared with supervised paradigms, it

remains limited in its ability to isolate learning-specific mechanisms (Janacsek et al., 2012; Szegedi-Hallgató et al., 2019). Since sequence elements are repeatedly practiced without interspersed random or noisy trials, improvements in RT may reflect both sequence learning and visuomotor performance improvement. In other words, faster and more accurate responses may reflect visuomotor improvement effects rather than learning of the underlying sequence structure. In classical SRT tasks, sequence learning is typically inferred from progressively faster RTs across training and from marked increases in RTs when the sequence is unexpectedly altered (Nissen & Bullemer, 1987). Consequently, it remains uncertain whether reported impairments in OCD reflect genuine deficits in unsupervised deterministic learning or are confounded by visuomotor factors.

A further limitation is that deterministic SRT tasks may promote explicit awareness of the repeating sequence (Remillard, 2003, 2014). In individuals with OCD, such awareness can trigger strategies that extend beyond implicit learning (Soref et al., 2018, 2021). Compared with neurotypical participants, several studies have found that individuals with OCD are more likely to develop explicit knowledge of the task structure (Goldman et al., 2008; Marker et al., 2006). Importantly, explicit sequence learning itself appears to be preserved across levels of OC symptoms (Barzilay et al., 2022), suggesting that the involvement of explicit processes does not necessarily reflect impaired explicit learning. This tendency has been linked to greater reliance on controlled processing and heightened attention to task structure, potentially encouraging pattern search and strategic responding in paradigms intended to assess implicit learning (Goldman et al., 2008; Marker et al., 2006; Soref et al., 2008, 2018, 2021). Consistent with these findings, neuroimaging studies indicate greater engagement of hippocampal and orbitofrontal regions during SRT performance in OCD (Rauch et al., 1997, 2007), regions not typically engaged during classical SRT performance in healthy participants (Janacsek et al., 2020). Together, these findings suggest that deterministic SRT performance in OCD may involve additional explicit or strategic processes, complicating the interpretation of observed learning differences (Deckersbach et al., 2002; Rauch et al., 2007; Soref et al., 2021; Ullman & Pullman, 2015).

Importantly, evidence from another SL paradigm suggests that implicit learning may remain intact in OCD when task demands reduce the contribution of explicit strategies. Using a modified Artificial Grammar Learning (AGL) task, Soref et al. (2021) found comparable implicit learning in individuals with OCD and healthy controls. In this paradigm, participants were exposed to stimulus sequences generated according to an underlying grammatical structure and subsequently classified novel sequences according to whether they conformed to the previously encountered regularities (Soref et al., 2021). These findings suggest that impairments reported in deterministic SRT studies may not reflect a generalized deficit in implicit regularity learning, but may partly depend on the type of regularity being acquired and the cognitive processes recruited by the task. However, whether the implicit acquisition of probabilistic transitional regularities is altered in relation to OC characteristics remains largely unknown, motivating the use of paradigms that allow such learning to be examined directly.

1.6. Learning in the noise: Alternating Serial Reaction Time task

To overcome the theoretical and methodological limitations of deterministic SRT paradigms, the Alternating Serial Reaction Time (Farkas et al., 2023; Howard & Howard, 1997) task provides a promising alternative. The ASRT is a four-choice visuomotor learning task in which sequential regularities are interleaved with random elements, creating a probabilistic structure with transitional probabilities below 1 (Farkas et al.,

2023; Howard & Howard, 1997). This structure reduces the likelihood of explicit awareness (Horváth et al., 2022; Vékony et al., 2022) and allows for a more selective assessment of implicit SL while minimizing confounds related to visuomotor practice and strategic behavior (Janacsek et al., 2012). Importantly, among SL paradigms, it provides a relatively process-pure measure of probabilistic learning, capturing learning mechanisms with minimal contamination from non-learning processes (Janacsek et al., 2012; Nemeth & Tóth-Fáber, 2026). Its probabilistic structure also more closely resembles everyday learning, where regularities must often be extracted from variable and noisy input rather than from fully predictable sequences.

During the task, a visual stimulus appears at one of four horizontally arranged spatial locations on a computer's screen, and participants are required to respond as quickly and accurately as possible by pressing the corresponding key. Unbeknownst to participants, stimuli follow a probabilistic eight-element sequence, alternating between pattern and random elements (e.g., 2 – r – 4 – r – 3 – r – 1 – r, where “r” denotes a random location and numbers indicate predetermined positions from left to right). The alternating structure of the task produces runs of three consecutive stimuli, known as triplets, in which some triplets occur with higher probability (high-probability triplets) and others with lower probability (low-probability triplets). High-probability triplets are more predictable due to their higher chance of occurrence, allowing participants to respond faster and more accurately, whereas low-probability triplets are less predictable and elicit slower and less accurate responses. Differences in RT and accuracy for high- compared with low-probability triplets are used to operationalize SL (Farkas et al., 2023; Howard & Howard, 1997; Pedraza et al., 2024). At the same time, general changes in reaction time across practice provide a separate measure of visuomotor performance, allowing learning-specific and general practice-related effects to be examined independently. These properties make the ASRT particularly suitable for examining unsupervised probabilistic learning in relation to OC tendencies and form the methodological basis of Studies 2 and 3.

1.7. Beyond learning: updating predictive representations

Learning is a complex, multi-component process that extends beyond the initial acquisition of information to encompass its maintenance and continuous updating. This is particularly critical in volatile environments, where previously acquired representations may no longer accurately predict subsequent events and must be updated accordingly (Shaqiri et al., 2013). Under such conditions, previously acquired responses, including those automatized through SL, must be adjusted to align with the altered environment, requiring the continuous updating of internal predictive representations. Habits and automatized behaviors formed via SL are known to develop robust and enduring representations over both short and long timescales (Ashby et al., 2010; Carden & Wood, 2018; Horváth et al., 2022; Kóbor et al., 2017).

The flexible use of previously acquired information may be particularly relevant to OCD. Evidence from outcome-devaluation and contingency-degradation paradigms indicates reduced adjustment of behavior when previously learned action-outcome relationships change (Gillan et al., 2011, 2014; Vaghi et al., 2019). This notion is reinforced by the habit hypothesis of OCD, which indicates that previously learned information may become excessively rigid and resistant to updating. Individuals with OCD are thought to persist in applying prior knowledge even when it is no longer relevant, highlighting the inflexibility of automatized responses and the difficulty of disengaging from them (Gillan et al., 2011, 2014; Vaghi et al., 2019). Notably, following

contingency degradation, individuals with OCD showed intact explicit knowledge of action–outcome relationships despite reduced behavioral sensitivity to changes in these relationships (Vaghi et al., 2019). A different perspective is provided by computational accounts, which suggest increased uncertainty about learned contingencies and reduced reliance on previously acquired information in OC symptoms (Fradkin, Adams, et al., 2020; Fradkin, Ludwig, et al., 2020). Recent findings in clinical OCD further indicate altered sensitivity to prediction errors when learning in volatile environments (Hoven et al., 2024). Together, these findings suggest that OCD-related alterations may concern not only what is learned, but also how previously acquired information guides behavior when environmental conditions change. However, it remains unclear whether similar alterations characterize statistical regularities acquired through unsupervised learning. Study 2 addressed this question by examining how previously acquired probabilistic regularities influence behavior following a change in environmental structure.

1.8. At what cost? - an interactive memory systems framework

SL and the updating of predictive representations cannot be fully understood in isolation when considering their contribution to OC tendencies. These processes interact with EFs, as EF and SL operate in parallel, draw on partially overlapping neurocognitive resources, and may compete for behavioural control (Ambrus et al., 2020; Pedraza et al., 2024; Poldrack et al., 2001; Vékony, Brezóczi, et al., 2025). In this context, adaptive behaviour depends on the flexible balance between automatic and goal-directed behaviour (Horváth et al., 2025; Poldrack et al., 2001). While SL and automatic processes rely predominantly on subcortical circuits, including the basal ganglia and striatum (Ashby et al., 2010; Janacsek et al., 2020), EF relies more strongly on prefrontal networks supporting goal-directed control (Diamond, 2013; Friedman & Robbins, 2022; Miyake et al., 2000). Within this interactive memory-systems framework, SL and EF are tightly coupled, and stronger engagement of automatic learning is often accompanied by reduced reliance on executive control, reflecting a dynamic trade-off between these systems (Horváth et al., 2022; Pedraza et al., 2024; Poldrack et al., 2001).

This reciprocal relationship can be examined at different levels (Horváth et al., 2025). Converging evidence suggests that these interactions can be either competitive or cooperative, depending on task demands and context. At the process level, automatic and goal-directed processes can be assessed within the same task, allowing their interaction to be observed at the state level. Such approaches have been central to the habit hypothesis of OCD (Gillan et al., 2011; Gillan, 2021; Gillan & Robbins, 2014). Under conditions of competition, stronger automatic responding may occur at the expense of goal-directed control when both systems are simultaneously engaged. However, these paradigms primarily capture within-task dynamics, leaving open whether this imbalance extends across contexts. A complementary approach is to assess SL and EF using separate tasks and examine associations across tasks and between their performance indices. Such correlational designs target more stable, trait-like differences and can reveal longer-term functional strategies of the brain (Horváth et al., 2025). For instance, reduced efficiency of prefrontal, EF-related processes may be accompanied by a compensatory reliance on automatized learning mechanisms (Ambrus et al., 2020; Pedraza et al., 2024). In OC research, this approach is particularly informative, as it can capture individual differences in the relative dominance of automatic versus executive control systems. A central open question is whether the imbalance between goal-directed and habitual processes is task-specific or reflects a more general characteristic across contexts. Investigating the

functional interaction between EF and SL is therefore critical for understanding OC-related behaviour.

Investigating the relationship between EF and SL therefore requires considering which components of executive control may be particularly relevant to OCD. Multiple models of EF have been proposed, many converging on three core components: working memory updating, inhibitory control, and cognitive flexibility (Bari & Robbins, 2013; Diamond, 2013; Friedman & Robbins, 2022; Miyake et al., 2000). Cognitive flexibility, in particular, refers to the capacity to adapt behaviour and thought in response to changing goals, rules, or environmental demands, supporting strategy shifting and the updating of mental representations. Impairments in cognitive flexibility are among the most robust and consistently reported cognitive markers of OCD and OC tendencies, suggesting that alterations in this function may serve as a key neurocognitive marker (Chamberlain et al., 2007; Tomiyama et al., 2019; Vaghi et al., 2017). This raises a critical question: how does reduced cognitive flexibility relate to the operation of SL, and more broadly, to the balance between automatic and goal-directed control? Experimentally, cognitive flexibility is commonly assessed using tasks such as the Card Sorting Test, set-shifting paradigms, or task-switching paradigms, which require participants to modify responses based on changing rules or feedback (Barceló, 1999; Fox et al., 2013; Miles et al., 2021; Nyhus & Barceló, 2009). Building on this framework, Study 3 examined cognitive flexibility, a prefrontal cortex-dependent function, using the Card Sorting Task (Fox et al., 2013). The study investigated its relationship with SL, with the aim of clarifying how interactions between EF and unsupervised SL contribute to maladaptive behavioural patterns of OC phenomena.

2. Study aims and research questions

Building on contemporary neurocognitive models of OCD and advances in learning theory, the present dissertation aims to elucidate unsupervised learning and its relationship with goal-directed control functions across the spectrum of OC tendencies. Rather than examining learning processes in isolation, this work adopts an integrative perspective to investigate how learning, updating, and executive control relate to OC tendencies. Study 1 critically reviews evidence from deterministic learning paradigms in OCD, disentangling specific components of task performance and their methodological limitations. Study 2 examines SL and the updating of previously acquired regularities in individuals with non-clinical OC tendencies. Study 3 investigates the relationship between SL and cognitive flexibility, addressing the broader balance between automatic learning and goal-directed control (Figure 1). Together, these studies provide complementary perspectives on learning and executive-control processes relevant to OC tendencies and OCD.

Accordingly, the dissertation addresses the following research questions:

- I. What do we know so far about unsupervised learning in OCD? – Study 1
- II. How do non-clinical OC tendencies influence individual differences in unsupervised statistical learning and the updating of predictive representations? – Study 2
- III. How do non-clinical OC tendencies modulate the dynamic interplay between statistical learning and cognitive flexibility? – Study 3

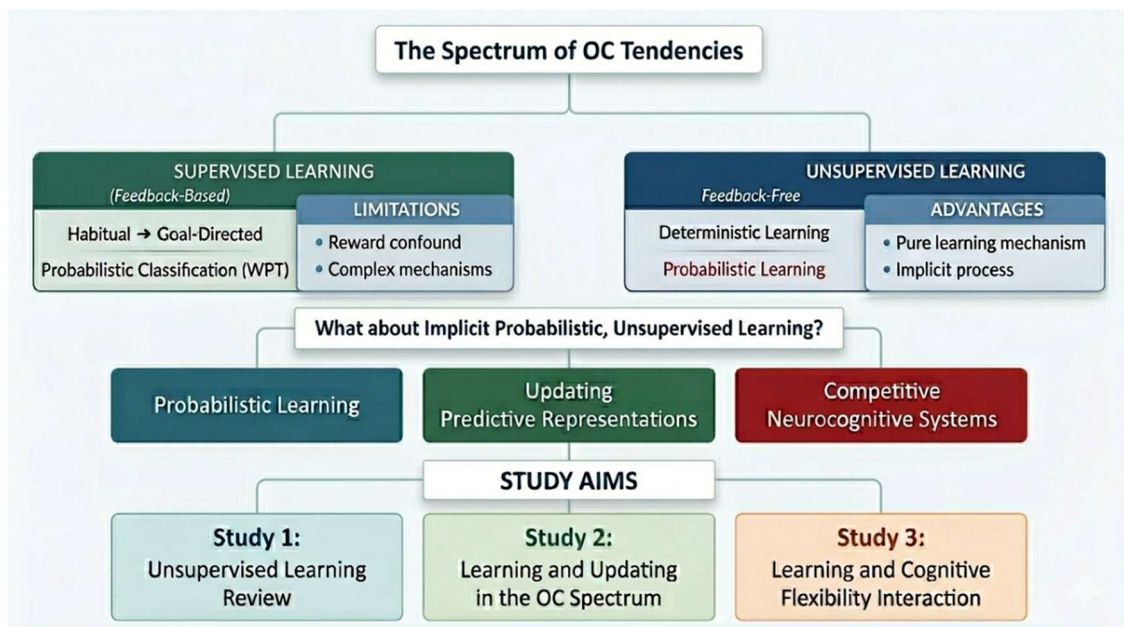


Figure 1. Theoretical framework of the neurocognitive models along the spectrum of OC tendencies and the integration of study aims. The figure illustrates the transition from supervised to unsupervised learning paradigms (e.g., feedback-based, habitual vs. goal-directed systems). It highlights the inherent limitations of feedback-driven models, such as reward-related confounds, while emphasizing the advantages of unsupervised learning as a pure, implicit process. The model establishes a trajectory for investigating implicit, probabilistic unsupervised learning as a key mechanism for updating predictive

representations within competitive neurocognitive systems. It outlines the study aims: Study 1 provides a systematic review of unsupervised learning; Study 2 investigates the probabilistic learning and the updating of representation across the OC spectrum; and Study 3 explores the interaction between probabilistic learning and cognitive flexibility.

3. Study 1: What do we know so far about unsupervised learning in OCD?

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Unraveling sequence learning in obsessive–compulsive disorder

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Obsessive–compulsive disorder (OCD) is characterized by the presence of intrusive thoughts and engagement in rigid, repetitive behaviors. Current neurobiological models of OCD emphasize dysfunction of the frontal–striatal system. According to recent research, sequence-specific learning is supported by the globus pallidus, as well as the anterior parts of the putamen and caudate nucleus. Given the shared involvement of brain regions in OCD and sequence learning (SL), a key question is how this fundamental learning mechanism works in OCD. Our short review assembles and summarizes existing psychological and neuroscientific studies, with the aim of disentangling the distinct subcortical brain networks that underlie SL in OCD, thereby advancing the current understanding of its neurobiological models. Considering the significance of SL in the habit formation process, our insights may contribute to a more comprehensive understanding of OCD and pave the way for new and enhanced therapeutic approaches.

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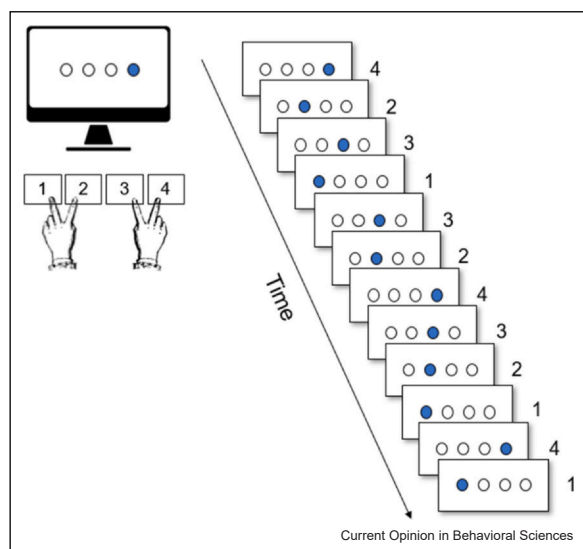
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Neurobiological models of obsessive–compulsive disorder

Obsessive–compulsive disorder (OCD) is characterized by persistent intrusive thoughts or beliefs (obsessions) and rigid, repetitive behavioral or mental acts (compulsions) [1]. Current neurobiological models of OCD emphasize structural and functional alterations in the frontostriatal regions, including the putamen [2–7], the caudate nuclei [2,5,8,9], the globus pallidus [10,11], the cerebellum [4,6,12–14], and the orbitofrontal and other prefrontal cortices [15–17]. These brain areas are also crucial in a fundamental cognitive process, that is, sequence learning (SL) [18]. SL underlies the information acquisition of serial ordering and regularities in the environment [19], either implicitly or explicitly. It underlies the development of automatic behaviors, including the formation of social, motor, and cognitive skills or habits [20–22]. The shared neural background has raised the question of how SL works in OCD.

Figure 1



A visual representation of the SRT task. In this task, participants usually see four locations (here white circles) arranged horizontally on a screen with a target stimulus appearing generally in one of the four locations (here blue circle). Participants are usually instructed to press the corresponding button to the location of the appearing stimuli (here 1, 2, 3, and 4 keys of a response device corresponding to the first, second, third, and fourth circle, from left to right, respectively). Unbeknown to the participants, the series of stimulus locations follow a predetermined sequence (in this case, a 12-item sequence: 4–2–3–1–3–2–4–3–2–1–4–1). It is important to note that this illustration is for explanatory purposes, as the SRT task employed in the reviewed studies differed in visual stimuli, sequence length, and task design.

Multiple studies endeavored to answer this question by using different adaptations of the Serial Reaction Time task (SRT [23]). The SRT task is a widely used visuomotor SL paradigm where participants are instructed to respond as quickly as possible to visual stimuli presented in a sequential manner (see Figure 1) [23,24]. The SRT task allows us to measure three aspects of learning: 1) sequence-specific learning, 2) visuomotor performance improvement, and 3) baseline reaction time (RT). Sequence-specific learning refers to the acquisition of predictable sequential patterns. The locations of the visual stimuli during the task follow a predefined sequence. The sequence includes either sequential (predictable) or randomized-location stimuli (unpredictable). Random elements can be introduced after a prolonged repetition of sequential elements or can alternate with sequential elements within blocks or throughout blocks. The sequence-specific learning effect is measured by the RT advantage on sequential trials or blocks over random ones. Improvement of visuomotor performance occurs through extensive practice [24] that can be assessed by the change in the participant's RT performance from the beginning to the end of the task. As a part of visuomotor performance, a baseline RT indicator

(i.e., an average RT score throughout the task) can also be accumulated from the participant's performance during the task.

By utilizing the three performance indicators, the SRT paradigm offers a comprehensive understanding of SL in OCD, facilitating the construction of an appropriate functional neurobiological model. A recent meta-analysis highlighted the involvement of the basal ganglia in SL, while also identifying different neurobiological regions associated with the abovementioned aspects of SL [18]. Implicit sequence-specific learning is associated with the functioning of the globus pallidus, the anterior and mid parts of the putamen, the caudate nucleus, and the nucleus accumbens. Since visuomotor performance improvement might encompass multiple subprocesses, such as sensorimotor integration and attention, beyond the basal ganglia, the premotor cortex and cerebellum are possibly involved [18]. Baseline RT performance exhibits substantial individual variability and depends on a variety of neurobiological and behavioral factors [25–27]. Previous studies employing the SRT paradigm to map SL in OCD failed to disentangle the three performance indicators related to different subcortical brain networks [28–31]. Hence, in this brief review, we aim to fill this gap by summarizing the existing articles using the SRT task to help establish a comprehensive functional neurobiological model of OCD in the future.

Sequence learning in obsessive-compulsive disorder

In the following, we will explore the results related to SL in OCD. The discussion will cover three key aspects: 1) sequence-specific learning, 2) visuomotor performance improvement, and 3) baseline RT. For each of these learning indicators, we will categorize the performance outcomes as follows: enhanced (showing better performance than controls), intact (demonstrating comparable learning effect to controls), reduced (exhibiting weaker learning than controls), or impaired (failing to exhibit the underlying regularities) (see Table 1). By reviewing behavioral performance, our objective is to ascertain the underlying nature of the subcortical regions associated with SL in OCD.

Regarding sequence-specific learning, three studies have detected intact performance in OCD with different adaptations of the SRT task [27,30,31]. One of them reported mixed results when they utilized a modified version of the SRT task, maximizing its implicitness with no response-to-stimulus interval [32]. Moreover, participants received different instructions: half of the OCD participants and half of their matched neurotypical controls were informed about the embedded pattern (intentional condition), while the others were simply instructed to respond as quickly and accurately as

Table 1**Summarizing the studies included in the review.**

Study	N (OCD-HC)	Performance indicator	Data reported	Result
Deckersbach et al. (2002) [34]	25–25	Sequence-specific learning	✓	Impaired
		Visuomotor performance improvement	✓	Intact
		Baseline RT	✓	Reduced
Goldman et al. (2008) ^a [28]	62–36	Sequence-specific learning	-	-
		Visuomotor performance improvement	✓	Intact
		Baseline RT	✓	Reduced
Kathmann et al. (2005) [33]	33–27	Sequence-specific learning	✓	Reduced
		Visuomotor performance improvement	✓	Intact
		Baseline RT	✓	Intact
Marker et al. (2006) ^b [29]	43–41	Sequence-specific learning	-	-
		Visuomotor performance improvement	-	-
		Baseline RT	✓	Reduced
Rauch et al. (1997) [30]	9–9	Sequence-specific learning	✓	Intact
		Visuomotor performance improvement	-	-
		Baseline RT	✓	Intact
Rauch et al. (2007) [31]	12–12	Sequence-specific learning	✓	Intact
		Visuomotor performance improvement	-	-
		Baseline RT	✓	Intact
Soref et al. (2018) ^c [27]	24–24	Sequence-specific learning	✓	Reduced
		Visuomotor performance improvement	✓	Reduced
		Baseline RT	✓	Reduced
Vloet et al. (2010) ^d [35]	20–25	Sequence-specific learning	✓	Impaired
		Visuomotor performance improvement	-	-
		Baseline RT	✓	Intact

^a In this study, the control group was provided by individuals diagnosed with non-OCD anxiety disorders and other anxiety disorders.

^b The task design makes it difficult to separate sequence-specific learning from visuomotor performance improvement in this study.

^c This study employed two learning conditions: standard and intentional. The table presents the outcomes pertaining to the implicit condition. Notably, all three learning indicators were intact in the intentional condition.

^d This study included children aged 10–18, in contrast to all the other articles that focused on adult populations (18–65 years).

possible (standard/incidental condition). Participants with OCD were able to acquire the embedded pattern; however, this different instructional condition resulted in different outcomes. In the incidental condition, their performance was reduced compared with controls, whereas it exhibited a significant enhancement when they were aware of the underlying sequence [27]. These findings suggest that the intentional condition was more beneficial for individuals with OCD. Similar to Soref's [27] incidental condition, individuals with OCD displayed reduced sequence-specific learning, as evidenced by their slight RT change in a random block after four consecutive sequential blocks [33]. This could indicate less-effective learning in OCD or limited shifting abilities. Furthermore, two studies reported reduced performance by employing specific designs to maximize implicit SL: one study applied only sequential patterns without random ones [29], while another study used two randoms at the beginning of each block [28]. However, this design lacks the ability to calculate the sequence-specific learning effect by extracting predictable and unpredictable trials, as done in prior studies [30,31,33,34]. In a dual-task design, incorporating a probabilistic sequence with a working memory task impaired implicit sequence-specific learning was observed in OCD [34]. Consistently, a pediatric study that examined SL in OCD has also demonstrated impaired

performance among boys with OCD [35]. In summary, the studies yielded conflicting results regarding sequence-specific learning in OCD: intact [27,30,31], reduced [27–29,33], or even impaired performance [34,35]. The inconsistencies are influenced by task design factors, such as the use of single or dual tasks, the duration of the response-to-stimulus interval, or most importantly, the level of sequence awareness. Future studies should systematically control these factors to gain a better understanding of these relationships.

Besides sequence-specific learning, there is less insight into the improvement in individuals with OCDs' visuomotor performance based on their RT change from the beginning to the end of the task. Some studies have found comparable visuomotor performance improvement between individuals with OCD and controls [28,33,34]. In the study of Soref et al. [27], the OCD group's RT improved in the progression of the task both in incidental and intentional conditions. Unfortunately, in a study where it seemed challenging to disentangle it from sequence-specific learning [29] and also due to the alternating block paradigm employed in some studies [30,31,35], it is not easy to draw any conclusions regarding visuomotor performance improvement. Nevertheless, the overall findings imply that individuals with OCD may exhibit intact visuomotor performance

improvement. When interpreting these results, it is crucial to consider various influencing factors, such as experimental design, task instructions, and individual characteristics.

The third performance indicator that could complement the better understanding of the result of visuomotor performance improvement is the participant's baseline RT during the task. Two approaches offer the opportunity to measure baseline RT. The first involves assessing several trials or blocks with completely randomized-location stimuli during the task [28–31,35] and the other approach is facilitated by the inherent characteristics of the task, wherein predefined sequential elements are integrated within randomized ones. Both strategies enable the distinct measurement of RTs for random trials, however, the latter has not been employed in any of the reviewed studies. Most studies reported similar performance to controls [30,31,33] but some have found it to be partly different [27,34,35] or even poorer [28,29]. Additionally, in Soref et al. [27], participants with OCD exhibited slower RTs during the incidental condition, while no significant differences were observed during the intentional condition in comparison to controls. This finding implies a potential preference for the intentional condition among individuals with OCD. The overall findings regarding baseline RT between OCD and controls yielded mixed results. Interpreting general RT performance should be approached as a supplementary measure to sequence-specific learning and visuomotor performance improvement, considering its multifactorial nature and individual variability.

Beyond the mixed results on the three SL performance indicators, neuroimaging procedures used during the SRT task make the model-building even more challenging. While neurotypicals display involvement of different subregions within the basal ganglia during the (implicit) SRT task [18], individuals with OCD exhibited primarily activation in the hippocampus, bilateral

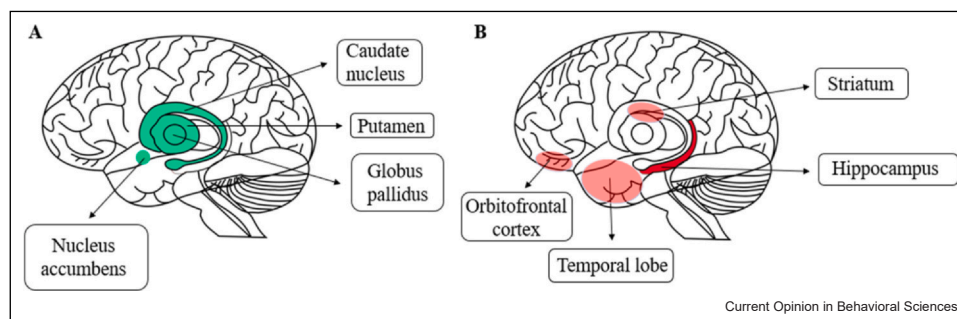
medial-temporal regions, and the orbitofrontal cortex during the task [30,31] (Figure 2). These brain regions were previously implicated in explicit, declarative memory processes [30,31,36], therefore, the engagement of explicit strategies during SL in OCD has been proposed [27,30,31,33,34]. Remarkably, the majority of studies assessed explicit knowledge after the SRT task [28–31,33,34], but in most instances, the task managed to remain implicit [30,31,33,34]. These findings raise additional questions regarding the underlying mechanisms of this fundamental learning process in individuals with OCD.

Theoretical consideration

For the future development of a comprehensive functional neurobiological model of OCD, gaining precise insight into SRT task performance is essential. Studies demonstrate heterogeneous results concerning the three behavioral indicators and neuroimaging data, hindering the establishment of clear conclusions and prompt extended considerations. Novel approaches hold the potential to enhance our understanding of SL in OCD from both neurobiological and behavioral perspectives. Initially, the aforementioned altered activation patterns observed during the SRT task in OCD imply the involvement of explicit processes associated with the medial-temporal region, as a possible result of basal ganglia dysfunction [27,30,31,34]. Recent investigations have indicated that the medial-temporal lobe and hippocampal regions potentially participate in processes such as the incidental extraction and consolidation of statistical serial information, or structures from the environment, such as SL [37–40]. This perspective may suggest that the observed activation patterns in OCD during the SRT task could represent a typical characteristic of the task.

On the other hand, the declarative memory hypothesis could provide a better explanation for this [41]. It posits that as long as the declarative memory system remains

Figure 2



Schematic illustration of disparities in brain regions between (a) healthy control subjects [18] and (b) individuals diagnosed with OCD [30,31] during the SRT task. It is important to mention that recent studies have indicated the involvement of the medial-temporal lobe and hippocampal regions in healthy individuals during SRT task [37,38].

relatively functional, it can effectively compensate for impaired basal ganglia-related processes, such as SL, across various disorders, including OCD, Tourette syndrome, autism spectrum disorder, specific language impairment, and dyslexia [22] as well as in Parkinson's disorder [42]. In OCD, the functionality and intact nature of declarative memory processes have been confirmed [28,29,33,34], rendering them eligible for taking over control in implicit processes [28,29,34]. Evidence comes from a study wherein the intentional/explicit instructional condition appeared to be more advantageous for individuals with OCD [27]. The dual-task design also supports this hypothesis when OCD participants failed on the SRT task while showing comparable results on frontotemporal-related tasks [34]. This suggests that the frontotemporal regions are already engaged, limiting their contribution to the success of SL. Thus, the accurate performance relies on an interplay between these brain networks, and therefore in a dual-task condition, one process is likely to succeed [43–46]. In summary, as a potential consequence of basal ganglia dysfunction in OCD, implicit memory processes may rely more on compensatory activation in the medial-temporal lobe. Considering the comparable improvement in visuomotor performance and baseline RT in OCD also suggests a facilitating role of the cerebellum and premotor cortex in more complex performances [18].

Besides the SRT task, implicit learning has mainly been investigated in OCD through the Weather Prediction Task (WPT) [47–50] and Card Betting Games [51], Pursuit Rotor Task [52], and Artificial Grammar Learning Task [53]. Similar to the SRT task, these investigations have also yielded inconsistent outcomes concerning behavioral performance: enhanced [52], intact [47–50,53], and impaired [51] implicit learning. However, individuals diagnosed with OCD also showed increased striatal and hippocampal activity during the WPT, while demonstrating intact performance at the behavioral level [47]. The available results on implicit learning tasks generally indicate intact learning in individuals with OCD. This raises the question regarding the factors that might influence implicit learning performance in OCD.

It can be presumed that the variations in results across different studies are influenced not only by task design factors but also by individual differences, including symptom subtype and severity [28,31,54–56] or even specific temperament and character dimensions [57–60] among people with OCD. Acknowledging that OCD is not a unitary condition [54,56,61–63], the diverse range of symptom dimensions and severities can be attributed to partially distinct neurobiological processes [62,64]. For instance, individuals with the washing subtype might exhibit reduced activation in the caudate nucleus and putamen, whereas individuals with the checking

subtype might show reduced hippocampal and temporal gray matter volumes [55,64,65]. These discrepancies might provide an explanation for the variations in performance regarding implicit SL. In certain conditions, individuals with OCD could perform on SL similarly to healthy controls, even employing compensatory strategies [30,31]. If we were to postulate that distinct symptom clusters draw their capacity for intact implicit SL from the temporal and hippocampal regions, we could potentially utilize this capability in designing therapeutic interventions. If an individual exhibits reduced or impaired implicit SL, it is imprudent to base therapeutic strategies solely on that. To achieve enduring therapeutic success, we might need to establish individualized therapeutic approaches tailored to the patient's strengths or weaknesses.

Future directions

In order to address the theoretical inquiries and achieve a comprehensive understanding of OCD at both the behavioral and neurobiological levels, certain methodological considerations should be taken into account in future research. The primary objective of this review was to elucidate SL in OCD by disentangling three distinct types of learning performance. However, this aim proved challenging as only a limited number of articles reported on all three indicators simultaneously [33,34]. Their results also need to be treated with caution, as the classic SRT paradigm fails to provide a precise separation between sequence-specific learning and visuomotor performance improvement. To deepen our comprehension of SL in OCD and overcome the limitations of a classic SRT task, an alternative version, known as the Alternating Serial Reaction Time (ASRT) task [66], could offer a potential solution. Unlike the classic SRT task, the ASRT task incorporates predetermined sequential elements within random ones, resulting in the alternation of random and sequential elements within a single block. This modified task not only allows for the calculation of sequence-specific learning by measuring the difference between predictable and unpredictable stimuli but also enables the separate assessment of visuomotor performance improvement and general RT [67]. The complete implicitness of the task has been widely confirmed [68,69] as well as its high reliability [70]. In future investigations, the adoption of this paradigm alongside electroencephalographical (EEG) or magnetoencephalographical (MEG) methodology [71] can provide insights into the neurobiological and behavioral aspects of implicit SL, particularly in terms of understanding the interactions and dynamics of subcortical regions in OCD during incidental information acquisition. To advance toward future studies implementing SRT, it is imperative for researchers to address symptomatic dimensions and symptom severity, encompassing not only personality types but potentially also temperament and

character dimensions. Additionally, researchers should consider broadening their focus in OCD research to encompass subclinical populations.

Conclusion

Gaining an understanding of SL is paramount in the construction of a neurobiological model for OCD. Through this concise review, our aim was to underscore the significance of subcortical areas in SL and highlight its relevance to OCD. Considering that SL plays a pivotal role in habit formation, obtaining a comprehensive understanding of its neurobiological and behavioral dimensions holds potential for the advancement of novel individualized therapeutic interventions in the future.

CRedit authorship contribution statement

Bianka Brezóczi: Conceptualization, Writing – original draft, Writing – review & editing. **Teodóra Vékony:** Conceptualization, Writing – review & editing. **Orsolya Pesthy:** Writing – review & editing. **Eszter Tóth-Fáber:** Writing – review & editing. **Katalin Csigó:** Writing – review & editing. **Kinga Farkas:** Writing – review & editing. **Dezso Németh:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare no conflicts of interest.

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4. Study 2: How do OC tendencies influence individual differences in unsupervised statistical learning and the updating of predictive representations?

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The Supplementary Material for the publications can be found in Chapter 9.1.

RESEARCH

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Individual differences in probabilistic learning and updating predictive representations in individuals with obsessive-compulsive tendencies

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Abstract

Background Obsessive-compulsive (OC) tendencies involve intrusive thoughts and rigid, repetitive behaviours that also manifest at the subclinical level in the general population. The neurocognitive factors driving the development and persistence of the excessive presence of these tendencies remain highly elusive, though emerging theories emphasize the role of implicit information processing. Despite various empirical studies on distinct neurocognitive processes, the incidental retrieval of environmental structures in dynamic and noisy environments, such as probabilistic learning, has received relatively little attention.

Methods In this study, we aimed to unravel potential individual differences in implicit probabilistic learning and the updating of predictive representations related to OC tendencies in a non-clinical population. We conducted two independent online experiments ($N_{\text{Study1}} = 164$, $N_{\text{Study2}} = 256$) with university students. Probabilistic learning was assessed using an implicit visuomotor probabilistic learning task, involving sequences with second-order non-adjacent dependencies.

Results Our findings revealed that implicit probabilistic learning remained remarkably robust among OC tendencies within a non-clinical population. Furthermore, the results highlighted effective updating capabilities of predictive representations, which were not influenced by OC tendencies.

Conclusions These results offer new insights into individual differences in probabilistic learning and updating in relation to OC tendencies, contributing to theoretical, methodological, and practical approaches for understanding the maladaptive behavioural manifestations of OC disorder and subclinical tendencies.

Keywords Obsessive-compulsive tendencies, Obsessive-compulsive disorder, Probabilistic learning, Predictive processing, Individual differences, Statistical learning

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Introduction

During their morning routines, many people repeatedly check whether they have locked the front door or confirm that their wallet and phone are in their bag or pockets. Over time, these may become automatic, habitual actions. Such behaviours often reflect non-clinical tendencies of Obsessive-Compulsive Disorder (OCD) even in healthy individuals [1]. OCD is defined by the excessive and impeding presence of intrusive thoughts ('obsessions') and rigid, repetitive actions ('compulsions') [2]. Compulsive actions are perceived as irrational, with individuals desiring to stop but unable to control their impulses [2, 3]. This perspective suggests that, in the case of OCD, it is most appropriate to measure processes in which individuals already have—or can develop—explicit knowledge of their learning mechanisms. Therefore, studies have predominantly focused on more easily acquirable deterministic contingencies and supervised learning paradigms, including feedback or rewards [4–16]. However, in real life, individuals might extract hidden associative contingencies in the noisy environmental stream through an implicit, unsupervised way by mere exposure, that is, through probabilistic learning [17–20]. This process is particularly significant in OCD, as it also could contribute to the development and maintenance of habitual, repetitive actions in OCD and among obsessive-compulsive (OC) tendencies. This type of unsupervised learning remains poorly understood in OCD as well as among OC tendencies, hence, the current study aims to address this gap.

In supervised learning or reinforcement learning, participants receive feedback or reward for their performance throughout the task. Such paradigms used in OCD research are the probabilistic classification task [9–13], and associative supervised learning tasks [5, 7], where individuals with OCD have generally demonstrated intact performance [9–11] for exceptions see: [12, 13]. Previously, a few unsupervised learning studies have sought to uncover implicit learning processes (for a review, see [25]), with most revealing weaker performance in OCD [21–27] for exceptions, see: [28–31]. However, the application of fixed deterministic contingencies has recently been emphasized as a key weakness of these studies (for a review, see: [21]). The fundamental issue with previous approaches is that they do not allow clear dissociation between reward/feedback processing and pure learning processes. This is a critical limitation because one of the key open questions is whether the core deficit lies in reward/feedback processing or learning itself. Our study aimed to address this question by employing a learning paradigm that does not involve supervision. In our case, this was implemented by omitting reinforcement for the specific sequence, effectively creating an unsupervised learning condition. Moreover, to ensure the complete

implicitness of the learning process and overcome the limitations of previous studies, we employed sequences with second-order non-adjacent dependencies, allowing us to measure how OC tendencies influence the ability to implicitly learn hidden probabilistic patterns from the noisy environment [19, 32]. Since our environment is constantly changing, it is also essential to assess the stability of the established predictive representations and the ability to effectively update them in response to volatile situations. Prominent theories based on supervised methods propose that individuals with OCD tend to rigidly stick to previously learned information and find it difficult to update their behaviour when facing a novel condition [5, 7, 8]. Another recent theory similarly emphasizes the role of uncertainty and pervasive doubt about previously acquired knowledge, leading individuals to rely on the most recent outcomes, thereby generating highly exploratory and distrustful behaviour [33, 34]. Both theories imply that individuals with OCD or OC tendencies face challenges in updating their behaviour, however, neither theoretical model elucidates the updating of predictive representations arising from the incidental learning of probabilistic contingencies. The environment can subtly and unconsciously shift, prompting unaware behavioural updates. This requires the ability to adjust predictive representations accordingly. Nonetheless, this ability has not yet been examined in the context of OCD and OC tendencies. Thus, our question is: to what extent do OC tendencies contribute to the resistance and updating capability of predictive representations in a volatile environment, in an unsupervised manner?

Investigating learning and updating in OCD is crucial, and most of the aforementioned findings have been conducted primarily with clinically diagnosed OCD patients. However, numerous studies increasingly support a dimensional understanding of OCD over dichotomous categories [1, 35–39]. This approach emphasizes the presence of subclinical OC tendencies or traits in the general population and their manifestations in behavioural variability and brain structures (1,36–40). Furthermore, it has been suggested that examining non-clinical samples could offer insights into aspects of the continuum that connect subclinical OC tendencies to clinically severe OC symptoms [1, 35–39]. In this regard, we lack information on how OC tendencies are associated with potential individual differences in the acquisition of probabilistic contingencies and the resilience or updating of predictive representations. To overcome the limitations of prior studies, we aim to assess implicit probabilistic processes using a visuomotor statistical learning task with second-order non-adjacent dependencies, that represents acceptable reliability and construct validity [45]. We conducted two online experiments involving non-clinical samples ($N_{\text{Study1}} = 164$, $N_{\text{Study2}} = 256$). In both

studies, OC tendencies are handled as a continuous spectrum, ranging from the lowest to the highest prevalence of OC tendencies. In Study 1, we aimed to pinpoint how OC tendencies contribute to potential individual differences in probabilistic learning, while in Study 2, to the resistance and updating of predictive representations in adjusting to a volatile condition.

Methods

Participants

Study 1 involved 224 university students who participated in an online experiment, for which they received course credit. To ensure data integrity, stringent quality control measures were employed, resulting in the exclusion of 60 participants who did not comply with instructions. We aimed to meet multiple criteria for data quality control, which is detailed in the flow chart of participant exclusion after data collection as illustrated in Supplementary Materials S1. This led us to conduct our analysis on 73.21% of the initial participants in Study 1. The final sample of Study 1 contained 164 participants (111 female, 48 male, and 2 non-specified, 3 declined to answer; $M_{\text{Age}} = 21.76$ years; $SD_{\text{Age}} = 5.21$ years).

In Study 2, 344 university students participated in exchange for course credit. Similar to Study 1, we ensured data integrity (see Supplementary Materials S1 for more details), leading to the exclusion of 88 participants, thus yielding a final sample of 256 (74.4%) individuals (189 female, 64 male, and 1 non-specified, 2 declined to answer, $M_{\text{Age}} = 22.5$ years; $SD_{\text{Age}} = 5.42$ years). Participants in both studies gave informed consent, and the studies obtained approval from the Research Ethics Committee of Eötvös Loránd University Budapest, Hungary (2021/504), under the principles of the Declaration of Helsinki.

Measures

Alternating Serial Reaction Time task

To assess probabilistic learning, we employed a visuomotor learning paradigm, the Alternating Serial Reaction Time (ASRT) task that demonstrates acceptable reliability [40, 41]. The task was created in JavaScript using the jsPsych library version 6.1.0 [42, 43]. Participants encountered a visual stimulus, represented by a drawing of a dog's head, displayed in one of the four positions arranged horizontally on the computer screen. Their goal was to quickly and accurately identify the location of the target stimulus by pressing the corresponding key on the keyboard ("S", "F", "J", or "L" keys from left to right, respectively) (Fig. 1A). Stimuli remained visible until a correct response was provided, followed by a 120 ms response to stimulus interval before the next stimulus appeared. In the event of an incorrect response, the target stimulus remained present until a correct response was provided.

Without the participants' awareness, the stimuli adhered to a probabilistic eight-element sequence, alternating between pattern and random elements (e.g., 2 - r - 4 - r - 3 - r - 1 - r, where "r" denotes a random location, and the numbers signify predetermined positions from left to right). The task incorporated an alternating structure where some runs of three consecutive elements were more predictable (high-probability triplets) than others (low-probability triplets). A trial denotes a single element within the sequence, which can be either a pattern or a random element, and notably, it serves as the final element in a high- or low-probability triplet. For instance, in a sequence like 2-r-4-r-3-r-1-r, triplets such as 2-X-4, 4-X-3, 3-X-1, and 1-X-2 (where X represents the middle element of a triplet) occurred more frequently than triplets, such as 2-X-1 or 3-X-2, as their first and third elements could belong to either a pattern or random trial (Fig. 1B). High-probability triplets could be produced through the inclusion of either two pattern trials and one random trial in the center (occurring in 50% of trials), or by incorporating two random trials and one pattern trial in the center (occurring in 12.5% of trials). The remaining trials were categorized as low-probability triplets, with the final element appearing as random (occurring in 37.5% of trials) (Fig. 1B).

In Study 1, the ASRT task comprised 25 blocks, encompassing 10 repetitions of an eight-element sequence, resulting in 80 stimuli within each block (Fig. 1C). After completing each block, participants received individual feedback on their average accuracy and reaction time, but no feedback was given on their learning performance (as they were not aware that the task involved the learning of a regularity).

In Study 2, we utilized the same task structure but modified the task design. In the first part, 15 blocks were recorded, resulting in 1200 trials (hereafter referred to as the Learning phase). During this phase, participants learned and practiced a predetermined probabilistic sequence (Sequence A: e.g., 2-r-4-r-3-r-1-r). This phase was followed by a delay period ($M = 46.2$ min, $SD = 19.5$). After the break, the second part of the task commenced, involving another 15 blocks, from Block 16 to Block 30 (1200 trials). In Block 16–20, participants were reintroduced to the original, well-learned sequence from the previous phase (Sequence A). However, in Block 21–25, without any prior warning, we changed the sequence structure (i.e., Interference phase). We gave participants the reversed version of the original sequence (e.g., Sequence A: 2-r-4-r-3-r-1-r, Sequence B: 1-r-3-r-4-r-2-r). In Block 26–30, participants were presented the original sequence (A) again (Fig. 1D). The structural change in Block 21–25 resulted in some alterations in the probability of the triplets. Triplets that were high-probability during the Learning phase became low-probability

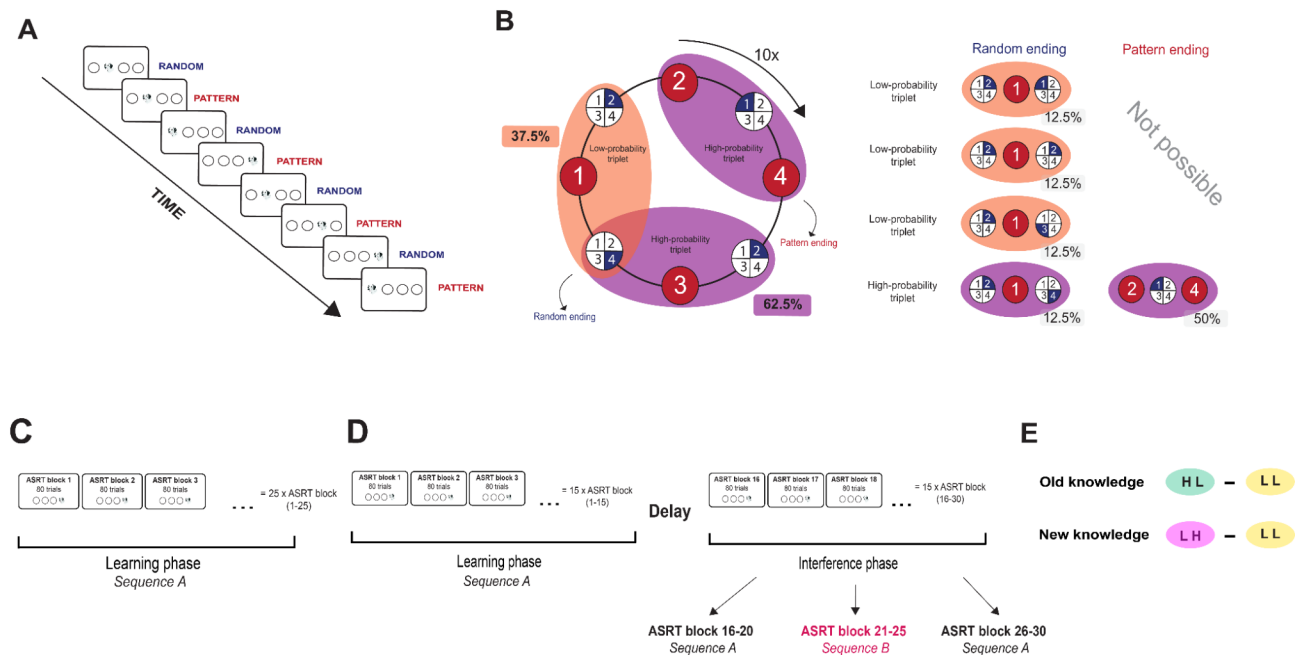


Fig. 1 ASRT Task Structure and Design. **A**. In the ASRT task, participants were required to press keys that matched the location of a target stimulus, represented by a dog's head. Every trial followed an 8-element probabilistic sequence. This sequence included random elements interspersed among the patterned elements, forming a series like 2-r-4-r-3-r-1-r, where the numbers indicate the locations of the pattern trials from left to right and 'r' signifies random positions. **B**. Formation of triplets in the ASRT task. Pattern elements, which consistently appear in the same positions throughout the task, are represented with red backgrounds. Random elements, chosen randomly from four possible positions, are shown with blue backgrounds. Each trial was categorized as the third element in a sequence of three consecutive trials (a triplet). The probabilistic sequence structure resulted in some triplets occurring more frequently (high-probability triplets) than others (low-probability triplets). For visualization purposes, only three triplets are highlighted in this subfigure: 2(P)-1(R)-4(P) as a pattern-ending high-probability triplet, 2(R)-3(P)-4(R) as a random-ending high-probability triplet, and 4(R)-1(P)-2(R) as a random-ending low-probability triplet. The formation of high-probability triplets could involve the occurrence of either two pattern trials and one random trial at the center, which occurred in 50% of trials, or two random trials and one pattern trial at the center, which occurred in 12.5% of trials. In total, 62.5% of all trials constituted the final element of a high-probability triplet, while the remaining 37.5% were the final elements of a low-probability triplet. **C**. ASRT task experimental design in Study 1. In Study 1, the ASRT task comprised 25 blocks, encompassing 10 repetitions of an eight-element sequence, resulting in 80 stimuli within each block. **D**. The ASRT task design in Study 2 involved multiple phases. In the Learning phase, participants were given the same sequence (Sequence A) across 15 blocks, with each block containing 80 trials. This was followed by a delay ($M = 46.2$ min, $SD = 19.5$), during which participants completed questionnaires. In the Interference phase, participants first practiced Sequence A again in Block 16–20. In Block 21–25, the underlying sequence was changed without warning to the reversed version of the original sequence (Sequence B). Finally, in Block 26–30, participants were re-exposed to Sequence A. **E**. Investigating updating in the Interference phase in Study 2. The structural change in Block 21–25 resulted in changes in the probability of certain triplets. Triplets that were high-probability during the Learning phase became low-probability during the Interference phase ('H L'), while those that were low-probability during the Learning phase became high-probability during the Interference phase ('L H'). Additionally, some triplets remained low-probability in both phases ('L L'). The difference between the frequencies of 'H L' and 'L L' triplets reflects the resistance of previously well-learned probabilistic information to new interfering information, referred to as 'Old knowledge'. Conversely, the difference in probabilities between 'L H' and 'L L' triplets indicates the robustness of new probabilistic information compared to previously learned information, referred to as 'New knowledge'.

during the Interference phase ('H L'), or they were low-probability during the Learning phase that became high-probability during the Interference phase ('L H'). There were also triplets that were low-probability in both conditions ('L L'). Due to the reversed nature of the sequence and the lack of overlap, the formation of 'H H' triplets was not possible [19]. With this design, in addition to assessing probabilistic learning and visuomotor performance improvement, we can also measure sensitivity to interfering information. Based on Horváth et al. [19], this can be achieved in two ways: the difference between performance on 'H L' and 'L L' triplets reflects the resistance of previously well-learned information to new, interfering information (referred to as 'Old knowledge'). Whereas

the difference between performance on 'L H' and 'L L' triplets indicates the robustness of new information compared to previously learned information, so-called 'New knowledge' (Fig. 1E).

Obsessive-Compulsive Inventory-Revised

The evaluation of OC tendencies involved the use of a self-report questionnaire designed to assess both the severity and nature of these symptoms. This questionnaire, known as the Revised version of the Obsessive-Compulsive Inventory (OCI-R; [44]), consists of 18 items rated on a 5-point Likert scale (0=Not at all; 4=Extremely). Participants were instructed to indicate how much each described experience bothered them over

the preceding month. The OCI-R demonstrates good psychometric properties, including strong test-retest reliability and internal consistency, across both clinical [44, 45] and non-clinical samples [46, 47]. The questionnaire has a maximum achievable score of 72 points [44–46]. In Study 1, the highest score was 58 ($M = 20.72$, $SD = 11.30$), while in Study 2, it was 51 ($M = 14.24$, $SD = 11.73$). The distribution of the participant's OC tendencies is illustrated in the Supplementary Materials (Figure S2.A (Study 1) and Figure S2.B (Study 2)).

Procedure

Both experiments were hosted by the Gorilla Experiment Builder platform (<https://www.gorilla.sc>) [48]. The experiments began with participants reading an informational briefing and giving their consent to participation. Following this, Study 1 proceeded with the ASRT task, where participants completed two practice blocks before engaging in 25 subsequent task blocks. The initial practice blocks consisted entirely of random trials, which were not analysed here. To evaluate participants' perception of any discernible patterns during the task, we administered inquiries after its completion, prompting them to report any patterns they noticed throughout the task. Following this, participants were questioned regarding their awareness of the concealed sequence upon completion of the ASRT task. Specifically, they were asked whether they detected any regularities or patterns during the task and to provide details if they did. None of the participants could accurately describe the alternating sequence, which means that the task could remain entirely implicit, as confirmed earlier [19, 32]. Subsequently, we assessed the prevalence of OC tendencies with the OCI-R, as well as some demographic questions about socioeconomic status, sleep, health, and handedness. Considering the online nature of the experiment, participants were presented with additional brief questions regarding the circumstances of task completion. This was aimed at controlling for any potential confounding variables in our analyses (as seen in Supplementary Materials S1).

In Study 2, after obtaining informed consent, participants proceeded with the ASRT task, starting with the Learning phase. During this phase, participants began with two practice blocks to familiarize themselves with the task, followed by 15 blocks. The practice phase consisted of two blocks of random stimuli, which were not included in the analyses. A delay period followed the Learning phase, during which participants completed various questionnaires, including the OCI-R and demographic questions about socioeconomic status, sleep, health, and handedness — this period lasted 46.2 min on average (± 19.5 SD). Following this, participants entered the Interference phase, where they did not perform any practice blocks and immediately proceeded to testing.

After completing Block 30, participants were asked if they noticed any patterns during the task and, if so, were prompted to recall them. Similar to Study 1, participants were presented with the same additional brief questions about the conditions under which they completed the experiment, as detailed in the Supplementary Materials S1, to ensure the integrity of the experimental data.

Data preparation and analysis

Data preparation, statistical analyses, and visualization were conducted using R 4.3.3 [49]. Concerning the data of the ASRT task, first, we categorized each trial based on whether they were the last element of a high- or low-probability triplet. We excluded responses that were not the first one for the given trial. Trials below 150 ms and above 1000 ms were also removed, as well as the responses below and above three absolute median deviations. Repetitions (e.g., 2-2-2, 1-1-1) and Trills (e.g., 2-1-2, 3-2-3) were removed from the analysis since participants may show faster motor response inclinations on these types of trials [50]. Furthermore, we removed the first two trials of each block, as they do not belong to any identified triplet type. Finally, incorrect responses were excluded from the reaction time (RT) analysis. In Study 1, these criteria necessitated the removal of 18.01% of trials for the learning analyses of accuracy and 25.74% for analyses of RTs. In the Learning phase of Study 2, 18.46% of trials for analyses of accuracy and 25.37% for analyses of RTs; and 17.95% of trials from the Interference phase for analyses of accuracy and 24.88% for analyses of RTs were removed.

Learning phase

We report performance indicators calculated from both RT and accuracy data. We introduce two distinct forms of learning: probabilistic learning and improvement in visuomotor performance. Probabilistic learning was calculated using the difference in RT/accuracy between high-probability and low-probability triplets. At the same time, visuomotor performance was operationalized by overall task RT/accuracy and its changes over time, indicated by faster/less accurate responses in later blocks, regardless of triplet probability. Initially, we assessed implicit probabilistic learning and its association with OC tendencies during the experiment's Learning phase.

Trial-level RT (log-transformed) and accuracy (coded as 0 for incorrect and 1 for correct) served as the outcome variables. We utilized Linear Mixed Models (LMMs) for analyzing RT, and Generalized Linear Mixed Models (GLMMs) for analyzing accuracy. Both LMMs and GLMMs were fit with the *mixed* function from the *afex* package ([51]). These models included fixed effects for Time (In Study 1: Factor: Block 1–5, Block 6–10, Block 11–15, Block 16–20, Block 21–25 and in Study 2

as Factor: Block 1–5, Block 6–10, Block 11–15), Triplet Type (Factor: High, Low), OC tendencies (OCI-R score), and their higher-order interactions. OCI-R score was a continuous variable, therefore, it was mean-centered. Please note that, although we used the OCI-R score as a continuous variable for all our analyses, for more illustrative data visualization, we depicted results at lower OC tendencies (Mean OCI-R score - SD) and higher OC tendencies (Mean OCI-R score + SD), based on standard deviations from the mean. The models also included participant-specific intercepts and correlated slopes for the within-subject variables of Time and Triplet Type, treated as random effects. In reporting the results, the main effects of Time is interpreted as improvement in visuomotor performance both on RT and accuracy, regardless of probabilistic patterns. Meanwhile, the main effect of Triplet Type is seen as an indicator of the amount of implicit probabilistic learning, and the interaction between Time and Triplet Type represents the temporal trajectory of probabilistic learning throughout the task. In the learning phase, the last level of the Time factor was always the reference: in Study 1, it was Block 21–25, whereas in Study 2, it was Block 11–15.

Hence, our models were structured according to the following general form in lmer syntax:

Reaction time: $(\text{Log})RT \sim \text{Time} * \text{Triplet Type} * \text{OCI-R score} + (\text{Time} + \text{Triplet Type} | \text{Participant})$.

Accuracy: $\text{Accuracy} \sim \text{Time} * \text{Triplet Type} * \text{OCI-R score} + (\text{Time} + \text{Triplet Type} | \text{Participant})$.

Interference phase

To evaluate updating, we incorporated an Interference phase within the task, as described in the “Alternating Serial Reaction Time task” section. In the Interference phase of Study 2, there was a change in the ASRT task structure. In Block 20–25, participants got the reversed version of the original sequence, which also led to some changes in the predictability of the triplets. In the Interference phase, we investigated two forms of learning: Old knowledge and New knowledge. Probabilistic learning is computed by comparing RT or accuracy between trials with changed occurrence probabilities (‘H L’ or ‘L H’) and trials with unchanged occurrence probabilities (‘L L’). The difference between ‘H L’ and ‘L L’ indicated the retention of previously learned knowledge (or Old knowledge), while the difference in RT or accuracy between ‘L H’ and ‘L L’ indicated the acquisition of New knowledge. This meant that participants were expected to show increasingly faster responses/higher accuracy in ‘L H’ and ‘H L’ trials compared to ‘L L’ trials in Block 20–25. ‘L L’ trials served as a baseline for these learning scores, controlling for general practice effects. Since ‘L L’ trials were

consistently low-probability across phases, no significant increase in accuracy was expected due to probability-based learning.

Similarly to the analysis of the Learning phase, Trial-level RT (log-transformed) and accuracy (coded as 0 for incorrect and 1 for correct) served as the outcome variables for the updating analysis. We utilized LMMs for analyzing RT, and GLMMs for analyzing accuracy. Models included fixed effects for Time (Factor: Block 16–20, Block 21–25, Block 26–30), Triplet Type (Factor: For ‘Old knowledge’ ‘H L’, ‘L L’, For ‘New knowledge’ ‘L H’, ‘L L’), OC tendencies (mean-centered OCI-R score), and their higher-order interactions. The models also included participant-specific intercepts and correlated slopes for the within-subject variables of Time and Triplet Type, treated as random effects. In reporting the results, the main effect of Time is interpreted as a change in visuomotor performance both on RT and accuracy, regardless of probabilistic patterns. While the main effect of Triplet Type is seen as an indicator of the amount of implicit probabilistic learning, the interaction between Time and Triplet Type represents the temporal trajectory of learning. In the interference phase, the last level of the Time factor was always the reference (Block 26–30). Please note that, for all our analyses, we used the OCI-R score as a continuous variable, but for more illustrative data visualization, we depicted results at lower OC tendencies (Mean OCI-R score - SD) and higher OC tendencies (Mean OCI-R score + SD), based on standard deviations from the mean.

For all analyses, we evaluated assumptions of linearity, homoscedasticity, and normality of residuals using scatter plots and QQ plots of residuals. The assumptions of linearity and homoscedasticity were satisfied for all models. However, some models exhibited non-normal residuals. Nonetheless, fixed effects estimates of LMMs and GLMMs are known to be highly robust against this particular assumption violation [52]. Therefore, we considered our models to be adequate. Sample sizes, including the total number of data points and sampling units, random effects estimates, Nakagawa’s marginal and conditional R^2 [53] and adjusted Intraclass Correlation Coefficients (ICCs) are consistently reported in the summary tables (see in Supplementary Materials S2–S9). Post-hoc contrasts were performed using the *emmeans* R package after regridding [54]. For fixed effects inference, we utilized Type III tests (for RT models) and Likelihood Ratio Tests (for accuracy models) by comparing nested models with and without the effect of interest. Figures were generated with *ggplot2* [55]. *P* values from all post-hoc tests were adjusted for multiple comparisons using the Šidák method [56]. Alpha level 0.05 was applied to all analyses, and all *p*-values are two-tailed. All data and code

required to reproduce the results of this study are available on the OSF repository (<https://osf.io/fae2z/>).

Results

How did obsessive-compulsive tendencies relate to probabilistic learning? - Study 1

The RT model indicated a statistically significant main effect of Time ($F_{(4,172.93)}=91.55$, $p<.001$), showing that participants' response times improved in subsequent blocks (Block 1–5: 375 ms, 95% CI = [369, 381]; Block 6–10: 371 ms, 95% CI = [366, 377]; Block 11–15: 363 ms, 95% CI = [358, 368]; Block 16–20: 355 ms, 95% CI = [350, 359]; Block 21–25: 349 ms, 95% CI = [344, 354]; (Block 1–5) - (Block 6–10) contrast $p<.005$, (Block 1–5) - (Block 11–15) contrast $p<.001$, (Block 1–5) - (Block 16–20) contrast $p<.001$, (Block 1–5) - (Block 21–25) contrast $p<.001$, (Block 6–10) - (Block 11–15) contrast $p<.001$, (Block 6–10) - (Block 16–20) contrast $p<.001$; (Block 6–10) - (Block 21–25) contrast $p<.001$, (Block 11–15) - (Block 16–20) contrast $p<.001$, (Block 11–15) - (Block 21–25) contrast $p<.001$; (Block 16–20) - (Block 21–25) contrast $p<.001$). There was a statistically significant main effect of Triplet Type ($F_{(1,159.69)}=306.70$, $p<.001$), with faster RTs for high-probability triplets than for low-probability triplets, indicating implicit probabilistic learning (High: 359 ms, 95% CI = [354, 364]; Low: 366 ms, 95% CI = [362, 371]). A statistically significant Time $\times$ Triplet Type interaction was observed ($F_{(4, 243525.33)}=20.83$, $p<.001$), which reflected an enhancement in implicit probabilistic learning as time progressed (Low – High contrast in Block 1–5: 3.59 ms, 95% CI = [2.13, 5.05]; in Block 6–10: 5.98 ms, 95% CI = [4.52, 7.43]; in Block 11–15: 8.16 ms, 95% CI = [6.74, 9.58]; in Block 16–20: 10.14 ms, 95% CI = [8.74, 11.53]; in Block 21–25: 9.95 ms, 95% CI = [8.86, 11.33]; (Block 1–5) - (Block 6–10) contrast $p<.113$, (Block 1–5) - (Block 11–15) contrast $p<.001$, (Block 1–5) - (Block 16–20) contrast $p<.001$, (Block 1–5) - (Block 21–25) contrast $p<.001$, (Block 6–10) - (Block 11–15) contrast $p<.186$, (Block 6–10) - (Block 16–20) contrast $p<.001$; (Block 6–10) - (Block 21–25) contrast $p<.001$, (Block 11–15) - (Block 16–20) contrast $p=.227$, (Block 11–15) - (Block 21–25) contrast $p=.412$; (Block 16–20) - (Block 21–25) contrast $p>.999$). The main effect of the OCI-R score was not significant ($F_{(1,161.99)}=0.95$, $p=.330$), indicating that OC tendencies were not associated with baseline reaction time. Changes in visuomotor performance were also intact along the OC-spectrum as presented by the absence of a statistically significant Time $\times$ OCI-R interaction ($F_{(4, 172.68)}=1.45$, $p=.220$). Additionally, no significant interaction was found for either the Triplet Type $\times$ OCI-R score ($F_{(1, 159.45)}=0.11$, $p=.736$) and Triplet Type $\times$ Time $\times$ OCI-R score ($F_{(4, 243622.68)}=1.66$, $p=.157$), which suggests that OC tendencies did not influence the amount and trajectory of implicit probabilistic learning

(Fig. 2A). The full list of fixed and random effect parameters can be found in Supplementary Table S3.

With regards to accuracy, the model resulted in a statistically significant main effect of Time ($\chi^2(4)=40.07$, $p<.001$), indicating that participants became less accurate in subsequent blocks (Block 1–5: 92.1%, 95% CI = [91.4, 92.7]; Block 6–10: 91.2%, 95% CI = [90.4, 91.8]; Block 11–15: 91.1%, 95% CI = [90.5, 91.8]; Block 16–20: 90.6%, 95% CI = [89.9, 91.2]; Block 20–25: 90.0%, 95% CI = [89.2, 90.7]; (Block 1–5) - (Block 6–10) contrast $p=.002$, (Block 1–5) - (Block 11–15) contrast $p=.009$, (Block 1–5) - (Block 16–20) contrast $p<.001$, (Block 1–5) - (Block 21–25) contrast $p<.001$, (Block 6–10) - (Block 11–15) contrast $p>.999$, (Block 6–10) - (Block 16–20) contrast $p=.296$; (Block 6–10) - (Block 21–25) contrast $p=.003$, (Block 11–15) - (Block 16–20) contrast $p=.177$, (Block 11–15) - (Block 21–25) contrast $p<.001$; (Block 16–20) - (Block 21–25) contrast $p=.136$). There was also a statistically significant main effect of Triplet Type ($\chi^2(1)=131.58$, $p<.001$), with higher accuracy for high-probability triplets than for low-probability triplets, demonstrating implicit probabilistic learning (High: 92.3%, 95% CI = [91.7, 92.8]; Low: 89.6%, 95% CI = [88.9, 90.3]). A statistically significant Time $\times$ Triplet Type interaction showed an improvement in probabilistic learning as the task progressed ($\chi^2(4)=21.89$, $p<.001$) (High – Low contrast in Block 1–5: 1.50%, 95% CI = [0.93, 2.06]; in Block 6–10: 2.60%, 95% CI = [1.97, 3.23]; in Block 11–15: 2.60%, 95% CI = [1.98, 3.22]; Block 16–20: 3.33%, 95% CI = [2.68, 3.98]; in Block 21–25: 3.56%, 95% CI = [2.88, 4.24]; (Block 1–5) - (Block 6–10) contrast $p=.032$, (Block 1–5) - (Block 11–15) contrast $p=.032$, (Block 1–5) - (Block 16–20) contrast $p<.001$, (Block 1–5) - (Block 21–25) contrast $p<.001$, (Block 6–10) - (Block 11–15) contrast $p>.999$, (Block 6–10) - (Block 16–20) contrast $p=.493$; (Block 6–10) - (Block 21–25) contrast $p=.164$, (Block 11–15) - (Block 16–20) contrast $p=.503$, (Block 11–15) - (Block 21–25) contrast $p=.167$; (Block 16–20) - (Block 21–25) contrast $p>.999$). The main effect of OCI-R score revealed that higher OC tendencies were associated with more accurate responses ($\chi^2(1)=5.08$, $p=.024$) Low OC tendencies: 90.3%, 95% CI = [89.4, 91.1]; High OC tendencies: 91.7%, 95% CI = [90.9, 92.4]. Similarly to the RT model, neither interaction involving the OCI-R score was statistically significant, indicating that OC tendencies did not substantially influence probabilistic learning or its dynamics as assessed by accuracy (Triplet Type $\times$ OCI-R score: $\chi^2(1)=0.27$, $p=.605$; Time $\times$ Triplet Type $\times$ OCI-R score: $\chi^2(4)=6.11$, $p=.191$) as seen in Fig. 2C. The full list of fixed and random effect parameters can be found in Supplementary Table S4.

To investigate the relationship between OC tendencies and probabilistic learning, we examined the correlation between the OCI-R total score and the difference

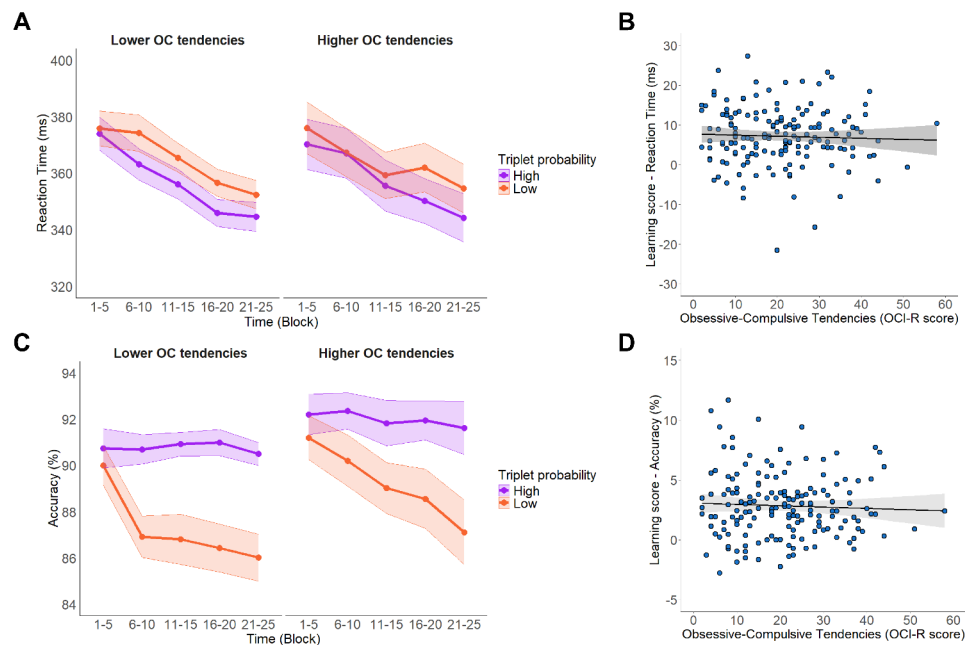


Fig. 2 Probabilistic learning performance metrics as a function of OC tendencies in Study 1 **A.** Probabilistic learning performance in terms of temporal trajectory (blockwise) reaction time. The orange line represents the responses to the low-probability triplets and the purple line represents responses to the high-probability triplets. Note that OC tendencies measured by OCI-R score was treated as a continuous variable in our analyses, but for more illustrative data visualization, we depicted results at Lower OC tendencies (OCI-R score: 20.73–11.33, on the left) and Higher OC tendencies (OCI-R score: 20.73 + 11.33, on the right) based on standard deviations from the mean. The x-axis indicates Time (Block 1–5, Block 6–10, Block 11–15, Block 16–20, Block 21–25), y-axis indicates RT (in ms). Participants also showed evidence of implicit SL, as they increasingly became faster for high-probability triplets than for low-probability triplets as the task progressed. However, OC tendencies did not influence either the amount, or the trajectory of learning. In all subfigures, points indicate means and error bars indicate SEM. **B.** Correlation between OC tendencies and difference learning scores based on reaction time for low- and high-probability triplets for the entire task. The correlation between probabilistic learning and OC tendencies in reaction time was not significant ($r(162) = -.029, p = .709$), indicating that OC tendencies do not relate to probabilistic learning as measured by reaction time. **C.** Probabilistic learning performance in terms of temporal trajectory (blockwise) mean accuracy. The orange line represents the responses to the low probability triplets and the purple line represents responses to the high-probability triplets. Note that OC tendencies were treated as a continuous variable in our analyses, but for more illustrative data visualization, we demonstrated results at Lower OC tendencies (OCI-R score: 20.73–11.33, on the left) and Higher OC tendencies (OCI-R score: 20.73 + 11.33, on the right) based on standard deviations from the mean. X-axis indicates Time [1–5], y-axis indicates mean accuracy (in %). Participants also showed evidence of implicit probabilistic learning, as they increasingly became more accurate for high-probability triplets than for low-probability triplets as the task progressed. However, OC tendencies did not influence the amount, nor the trajectory of learning. In all subfigures, points indicate means and error bars indicate SEM. **D.** Correlation between OC tendencies and difference learning scores based on accuracy for high- and low-probability triplets for the entire task. The correlation between probabilistic learning and OC tendencies in accuracy was not significant ($r(162) = -.035; p = .653$), indicating that OC tendencies do not relate to probabilistic learning as measured by accuracy

learning score. The difference score was calculated as the difference in median RT and mean accuracy between high- and low-probability trials across the task's temporal trajectory (Block 1–5, Block 6–10, Block 11–15, Block 16–20, Block 21–25), and then averaged across these five segments. Neither the correlation between probabilistic learning and OC tendencies in RT ($r(162) = -.029, p = .709$) nor in accuracy ($r(162) = -.035; p = .653$) was significant (Fig. 2B, D).

Summary of Study 1

In Study 1, we examined the relationship between the acquisition of probability-based structures and OC tendencies in a non-clinical population. We assessed implicit probabilistic learning with an unsupervised learning paradigm. Our results indicate that OC tendencies are not associated with individual differences in the acquisition

of implicit probabilistic information, as presented by the lack of significant interactions involving OCI-R score during our analyses. Overall, this result implies that probabilistic learning is unaffected among OC tendencies. Nevertheless, the complexity of learning renders it even more interesting to examine the updating ability of learned probabilistic representations, as behaviour is strongly influenced not only by the information learned but also by the ability to manipulate it, especially in terms of OC behavioural representations. Thus, in order to gain a deeper understanding of maladaptive behavioural patterns in OCD, in Study 2, we were interested in both the resistance of acquired predictive representations and their updating ability to a new condition among OC tendencies.

Results of Study 2

To evaluate the stability of the previously acquired information, in the Interference phase of Study 2, the task structure was changed. In Block 21–25, unbeknownst to the participants, we introduced the reversed version of the original sequence. For the analysis of this phase, we categorized triplets based on their predictability in the two sequences: ‘H L’ triplets had high-probability in the original sequence, but low-probability in the new sequence, ‘L H’ triplets had low-probability in the original sequence, but high-probability in the new sequence, and ‘L L’ triplets were low-probability in both, serving as a baseline during our analysis. Previously established knowledge (‘Old knowledge’) is represented by the performance difference between ‘L L’ and ‘H L’ triplets, while the acquisition of new probabilistic information (New knowledge) is measured by comparing the performance between ‘L L’ and ‘L H’ triplets.

To explore how OC tendencies affected the resistance to previously acquired knowledge (Old knowledge) and the adjustment to novel information (New knowledge), we used trial-level (log-transformed) RT and accuracy during the Interference phase as outcome variables. The fixed effects in the models included Time factor (Block 15–20, Block 21–25, Block 26–30), Triplet Type (for Old knowledge: ‘H L’, ‘L L’, and for New knowledge: ‘L H’ and ‘L L’), OCI-R score (as a continuous variable), and their interactions. Note that the main effect of Triplet Type and its interactions indicate differences in learning, while main effects and interactions excluding this factor can be interpreted as differences in visuomotor performance. Furthermore, the OCI-R score was treated as a continuous variable in our analyses. However, for more illustrative data visualization, we presented results at Lower OC tendencies (M-SD) and Higher OC tendencies (M+SD) based on standard deviations from the mean.

How did obsessive-compulsive tendencies modulate the resistance to previously acquired probabilistic information? - Old knowledge

In order to investigate the role of OC tendencies in updating predictive representations, we first also report performance in the Learning phase for both RT and accuracy. Then, we can properly interpret resistance to the acquired information. In terms of RT, the model yielded a statistically significant main effect of Time ($F_{(2,271.73)}=44.84$, $p<.001$), showing that participants became faster in subsequent Blocks (Block 1–5: 385 ms, 95% CI = [380, 389]; Block 6–10: 384 ms, 95% CI = [380, 388]; Block 11–15: 376 ms, 95% CI = [372, 380]; (Block 1–5) - (Block 6–10) contrast $p=.743$, (Block 1–5) - (Block 11–15) contrast $p<.001$, (Block 6–10) - (Block 11–15) contrast $p<.001$). There was a statistically significant main effect of Triplet Type ($F_{(1,250.03)}=181.05$, $p<.001$), with faster reaction

times for high-probability triplets than for low-probability triplets, indicating implicit probabilistic learning (High: 379 ms, 95% CI = [375, 383]; Low: 384 ms, 95% CI = [380, 388]). A statistically significant Time $\times$ Triplet Type interaction was observed ($F_{(2, 226324.76)} = 12.03$, $p < .001$), which reflected a temporal enhancement in implicit probabilistic learning (Low – High contrast in Block 1–5: 3.86 ms, 95% CI = [2.65, 5.08]; in Block 6–10: 5.05 ms, 95% CI = [3.83, 6.26]; in Block 11–15: 7.51 ms, 95% CI = [6.32, 8.71]; (Block 1–5) - (Block 6–10) contrast $p = .361$, (Block 1–5) - (Block 11–15) contrast $p < .001$, (Block 6–10) - (Block 11–15) contrast $p = .006$). Neither the main effect nor any interactions involving the OCI-R score were statistically significant, implying that OC tendencies did not influence implicit probabilistic learning. The full list of fixed and random effect parameters can be found in Supplementary Table S5.

In terms of Old knowledge, the RT model produced a statistically significant main effect of Time ($F_{(2,380.08)} = 102.42, p < .001$). Participants became generally slower after being exposed to the new sequence during Block 21–25 (Block 16–20: 350 ms, 95% CI = [346, 354]; Block 21–25: 361 ms, 95% CI = [358, 365]; Block 26–30: 363 ms, 95% CI = [359, 367]; (Block 16–20) - (Block 21–25) contrast $p < .001$, (Block 21–25) - (Block 26–30) contrast $p < .001$, (Block 21–25) - (Block 26–30) contrast $p = .089$). There was a statistically significant main effect of Triplet Type ($F_{(1, 269.72)} = 251.06, p < .001$), with faster reaction times to ‘H L’ triplets than to ‘L L’ triplets (‘H L’: 354 ms, 95% CI = [350, 358]; ‘L L’: 363 ms, 95% CI = [359, 366]). This suggests that, overall, participants maintained implicit knowledge of the old sequence despite being exposed to the new sequence. Additionally, the absence of a statistically significant Time $\times$ Triplet Type interaction ($F_{(2, 156913.57)} = 1.86, p = .156$) indicates that this resistance to interference was consistent across all Blocks. However, this resistance was not modulated by OC tendencies (Fig. 4A), based on the absence of statistically significant interactions involving the OCI-R score: (Time $\times$ OCI-R score: $F_{(2, 280.70)} = 2.56, p = .079$; Triplet Type $\times$ OCI-R score: $F_{(1, 270.58)} = 1.85, p = .174$; Time $\times$ Triplet Type $\times$ OCI-R score: $F_{(2, 156116.00)} = 1.42, p = .241$), as well as main effect of OCI-R score $F_{(1, 254.25)} = 0.81, p = .370$ (Fig. 3A). The full list of fixed and random effect parameters can be found in Supplementary Table S6.

For the accuracy indices, we first also report participants's performance in the Learning phase. Similar to RT the accuracy model resulted in a statistically significant main effect of Time ($\chi^2(2) = 56.66, p < .001$), showing that participants became less accurate in later blocks (Block 1–5: 92.8%, 95% CI = [92.3, 93.3]; Block 6–10: 91.4%, 95% CI = [90.9, 91.9]; Block 11–15: 91.1%, 95% CI = [90.6, 91.6]; (Block 1–5) - (Block 6–10) contrast $p < .001$, (Block 1–5) - (Block 11–15) contrast $p < .001$, (Block 6–10)

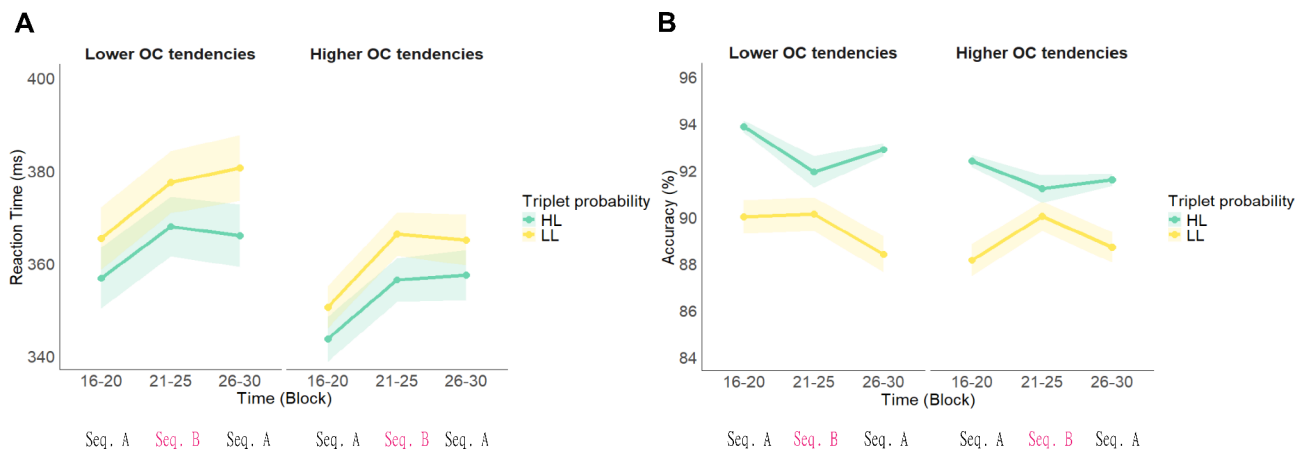


Fig. 3 Participants' performance during the Interference phase of Study 2 in terms of Old knowledge. **A.** Reaction time. The green line represents the responses to 'H L' probability triplets (triplets that were high-probability during the Learning phase but became low-probability during the Interference phase), and the yellow line represents the responses to 'L L' probability triplets (which were low-probability in both phases). The X-axis indicates Time (Block 16–20, Block 21–25, Block 26–30), the Y-axis indicates mean reaction time (in ms). Triplets are now categorized based on the changes in their predictability between Sequence A and Sequence B. Participants showed a resistance of previously acquired implicit knowledge to interference as they retained the performance difference between 'H L' and 'L L' triplets even after exposure to Sequence B. **B.** Accuracy. The green line represents the responses to the 'H L' probability (triplets that were high-probability during the Learning phase but became low-probability during the Interference phase), and the yellow line represents the responses to the 'L L' probability triplets (which were low-probability in both conditions). The X-axis indicates Time (Block 16–20, Block 21–25, Block 26–30), the Y-axis indicates mean accuracy (in %). Triplets are now categorized based on the changes in their predictability between Sequence A and Sequence B. Participants showed a resistance of previously acquired implicit knowledge to interference as they retained the performance difference between 'H L' and 'L L' triplets even after exposure to Sequence B in terms of accuracy. Note that, OC tendencies was treated as a continuous variable in our analyses, but for more illustrative data visualization, we exhibited results at Lower OC tendencies (OCI-R = 14.24–11.73, on the left) and Higher OC tendencies (OCI-R = 14.24 + 11.73, on the right) based on standard deviations from the mean. In all subfigures, points indicate means and error bars indicate SEM

- (Block 11–15) contrast $p = .256$). There was a statistically significant main effect of Triplet Type ($\chi^2(1) = 167.70$, $p < .001$), with higher accuracy for high-probability triplets than for low-probability triplets, evidencing implicit probabilistic learning (High: 92.8%, 95% CI = [92.4, 93.2]; Low: 90.7%, 95% CI = [90.2, 91.2]). Moreover, Time $\times$ Triplet Type showed a significant interaction, indicating improved probabilistic learning with time ($\chi^2(2) = 22.40$, $p < .001$), (High – Low contrast in Block 1–5: 1.36%, 95% CI = [0.95, 1.78]; in Block 6–10: 2.14%, 95% CI = [1.68, 2.59]; in Block 11–15: 3.13%, 95% CI = [2.66, 3.61]; (Block 1–5) - (Block 6–10) contrast $p = .246$, (Block 1–5) - (Block 11–15) contrast $p < .001$, (Block 6–10) - (Block 11–15) contrast $p = .004$). The main effect of OCI-R score indicated less accurate responses with a higher level of OC tendencies ($\chi^2(1) = 6.42$, $p = .011$; Low OC tendencies: 92.4%, 95% CI = [91.8, 92.9]; High OC tendencies: 91.3%, 95% CI = [90.6, 91.9]). However, in terms of visuomotor performance improvement, OC tendencies had no influence (Time $\times$ OCI-R score: $\chi^2(2) = 0.65$, $p = .725$). There was no interaction between Triplet Type $\times$ OCI-R score ($\chi^2(1) = 0.22$, $p = .635$), showing that the prevalence of OC tendencies did not influence the amount of implicit probabilistic learning. Meanwhile, a statistically significant Time $\times$ Triplet Type $\times$ OCI-R score interaction revealed that participants with higher OC tendencies demonstrated faster extraction of probability-based structures

($\chi^2(2) = 7.06$, $p = .029$) as assessed by accuracy: Lower OC tendencies: Block 1–5: 1.39%, 95% CI = [0.84, 1.94]; in Block 6–10: 1.70%, 95% CI = [1.09, 2.31]; in Block 11–15: 3.33%, 95% CI = [2.69, 3.97]; (Block 1–5) - (Block 6–10) contrast $p = .816$, (Block 1–5) - (Block 11–15) contrast $p < .001$, (Block 6–10) - (Block 11–15) contrast $p < .001$. Higher OC tendencies: Block 1–5: 1.33%, 95% CI = [0.75, 1.91]; in Block 6–10: 2.61%, 95% CI = [1.96, 3.27]; in Block 11–15: 2.90%, 95% CI = [2.22, 3.57]; (Block 1–5) - (Block 6–10) contrast $p = .007$, (Block 1–5) - (Block 11–15) contrast $p < .001$, (Block 6–10) - (Block 11–15) contrast $p = .899$). The full list of fixed and random effect parameters can be found in Supplementary Table S7.

The accuracy model regarding Old knowledge resulted in a statistically significant main effect of Time ($\chi^2(2) = 12.27$, $p = .002$): participants became less accurate in the upcoming blocks (Block 16–20: 92.1%, 95% CI = [91.6, 92.5]; Block 21–25: 91.4%, 95% CI = [90.9, 91.9]; Block 26–30: 91.3%, 95% CI = [90.9, 91.8]; (Block 16–20) - (Block 21–25) contrast $p = .018$, (Block 16–30) - (Block 26–30) contrast $p = .004$, (Block 21–25) - (Block 26–30) contrast $p = .982$). There was a statistically significant main effect of Triplet Type ($\chi^2(1) = 107.06$, $p < .001$), with higher accuracy for 'H L' trials than for 'L L' trials, indicating the resistance of the previously acquired information ('H L': 92.8%, 95% CI = [92.4, 93.2]; 'L L': 90.3%, 95% CI = [89.7, 90.8]). There was also a statistically significant

Time $\times$ Triplet Type interaction ($\chi^2(2) = 19.83, p < .001$), which stemmed from increasing probabilistic learning with the progression of the task ('H L' - 'L L' contrast in Block 16–20: 3.16%, 95% CI = [2.54, 3.78]; in Block 21–25: 1.41%, 95% CI = [0.67, 2.16]; in Block 26–30: 3.03%, 95% CI = [2.38, 3.68]; (Block 16–20) - (Block 21–25) contrast $p < .001$, (Block 16–20) - (Block 26–30) contrast $p = .984$, (Block 21–25) - (Block 26–30) contrast $p = .002$). OC tendencies did not influence the accuracy of responses in the Interference phase (OCI-R score main effect: $\chi^2(1) = 0.89, p = .347$), nor on the improvement of visuomotor performance (Time $\times$ OCI-R score: $\chi^2(2) = 2.07, p = .355$). The absence of Triplet Type $\times$ OCI-R score interaction indicates that OC tendencies did not modulate the resistance to previously acquired probabilistic information (Triplet Type $\times$ OCI-R score: $\chi^2(1) = 0.17, p = .677$), and the progression of learning (Time $\times$ Triplet Type $\times$ OCI-R score: $\chi^2(2) = 1.42, p = .491$) as assessed by accuracy (Fig. 3B). The full list of fixed and random effect parameters can be found in Supplementary Table S8.

How did obsessive-compulsive tendencies relate to the ability to acquire novel probabilistic information? - New knowledge

The RT model effectively identified the impact of exposure to the new sequence, leading to a statistically significant main effect of Time ($F_{(2, 267.81)} = 97.50, p < .001$), with participants becoming overall slower after the introduction of the new sequence in Block 21–25 (Block 16–20: 354 ms, 95% CI = [350, 358]; Block 21–25: 364 ms, 95% CI = [360, 368]; Block 26–30: 367 ms, 95% CI = [363, 371]; (Block 16–20) - (Block 21–25) contrast $p < .001$, (Block 16–20) - (Block 26–30) contrast $p < .001$, (Block 21–25) - (Block 26–30) contrast $p = .006$). There was a statistically significant main effect of Triplet Type ($F_{(1, 273.93)} = 11.92, p < .001$), with faster reaction times for 'L H' triplets than for 'L L' triplets ('L H': 361 ms, 95% CI = [357, 364]; 'L L': 363 ms, 95% CI = [359, 366]), which highlights that participants gained implicit knowledge of the new sequence. A statistically significant Time $\times$ Triplet Type interaction indicates the extraction of the new probabilistic information ($F_{(2, 109858.63)} = 3.82, p = .022$), (Low - High contrast in Block 16–20: 0.32 ms, 95% CI = [-1.47, 2.11]; in Block 21–25: 3.28 ms, 95% CI = [1.77, 4.78]; in Block 26–30: 2.63 ms, 95% CI = [0.76, 4.49]; (Block 16–20) - (Block 21–25) contrast $p = .017$, (Block 16–20) - (Block 26–30) contrast $p = .158$, (Block 21–25) - (Block 26–30) contrast $p = .909$). No main effect of OCI-R score ($F_{(1, 254.27)} = 0.78, p = .379$) or interaction involving OCI-R score was statistically significant, suggesting that OC tendencies did not modulate the acquisition of new implicit knowledge or visuomotor performance to interference during the interference phase of the experiment, as assessed by RT (Time $\times$ OCI-R score: $F_{(2, 269.49)} = 2.93, p = .055$; Triplet Type $\times$

OCI-R score: $F_{(1, 276.32)} = 1.80, p = .180$; Time $\times$ Triplet Type $\times$ OCI-R score: $F_{(2, 109860.25)} = 1.21, p = .299$) (Fig. 4A). The full list of fixed and random effect parameters can be found in Supplementary Table S9.

In terms of accuracy, participants became less accurate in subsequent blocks as indicated by a main effect of Time ($\chi^2(2) = 39.85, p < .001$). Block 16–20: 90.7%, 95% CI = [90.1, 91.3]; Block 21–25: 91.4%, 95% CI = [90.9, 91.8]; Block 26–30: 89.6%, 95% CI = [89.0, 90.2]; (Block 16–20) - (Block 21–25) contrast $p = .039$, (Block 16–20) - (Block 26–30) contrast $p = .003$, (Block 21–25) - (Block 26–30) contrast $p < .001$). There was a statistically significant main effect of Triplet Type ($\chi^2(1) = 6.58, p = .010$), with higher accuracy for 'L H' trials than for 'L L' trials, indicating the acquisition of the novel implicit knowledge ('L H': 90.9%, 95% CI = [90.4, 91.3]; 'L L': 90.3%, 95% CI = [89.8, 90.8]). There was also a statistically significant Time $\times$ Triplet Type interaction ($\chi^2(2) = 8.67, p = .013$), which resulted from a better acquisition of the novel information with Time ('L H' - 'L L' contrast in Block 16–20: 0.50%, 95% CI = [-0.13, 2.53]; in Block 21–25: 1.20%, 95% CI = [0.61, 1.80]; in Block 26–30: 0.04%, 95% CI = [-0.84, 0.76]; Block 16–20 - Block 21–25 contrast $p = .339$, Block 16–20 - Block 26–30 contrast $p = .672$, Block 21–25 - Block 26–30 contrast $p = .029$). Similarly to RT, OC tendencies did not influence mean accuracy in the Interference phase, as shown by a lack of significant main effect of OCI-R score ($\chi^2(1) = 1.67, p = .197$). Furthermore, it indicated no modulating effect on visuomotor performance (Time $\times$ OCI-R score interaction: $\chi^2(2) = 0.62, p = .733$), and nor did it influence the ability to obtain new probabilistic information (Triplet Type $\times$ OCI-R score: $\chi^2(1) = 1.26, p = .261$), or its temporal progression (Time $\times$ Triplet Type $\times$ OCI-R score: $\chi^2(2) = 1.01, p = .603$) as seen in Fig. 4B. The full list of fixed and random effect parameters can be found in Supplementary Table S10.

Summary of study 2

In Study 2, we took a step further by investigating how OC tendencies influence potential individual differences in the non-clinical population regarding the resistance to and updating of predictive representations when adapting to volatile conditions. To investigate the role of OC tendencies in updating predictive representations, it was fundamental to measure the acquisition of probability-based structures in Study 2, too. Our results demonstrated strong performance in learning; however, in terms of accuracy, higher OC tendencies were associated with faster extraction of probability-based structures. This suggests that while the amount of learning may not vary, individual differences in the pattern of learning could emerge among OC tendencies. In terms of updating, in contrast to prior studies [5, 7, 33, 34], participants in the present experiment were not notified about any

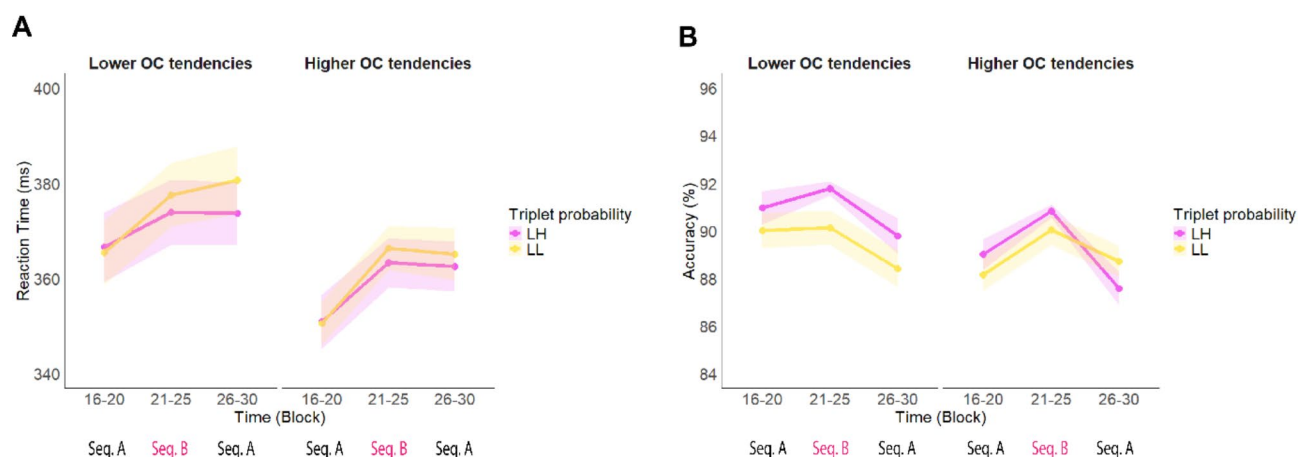


Fig. 4 Participants' performance during the Interference phase of Study 2 in terms of New knowledge. **A.** Reaction time. The pink line represents the responses to the 'L H' probability triplets (that were low-probability during the Learning phase but became high-probability during the Interference phase) and the yellow line represents the responses given to the 'L L' probability triplets (which were low-probability in both conditions). The x-axis indicates Time (Block 16–20, Block 21–25, Block 26–30), the Y-axis indicates mean reaction time (in ms). Triplets are now categorized based on the changes in their predictability between Sequence A and Sequence B. Participants showed a successful acquisition of novel implicit knowledge as they started to differentiate between 'L H' and 'L L' triplets in Sequence B, however, it was not modulated by the level of the OC tendencies. **B.** Accuracy. The pink line represents the responses to the 'L H' probability triplets (that were low-probability during the Learning phase but became high-probability during the Interference phase) and the yellow line represents the responses to the 'L L' probability triplets (which were low-probability in both phases). The x-axis indicates Time (Block 16–20, Block 21–25, Block 26–30), Y-axis indicates mean accuracy (in %). Participants demonstrated a successful acquisition of novel implicit knowledge as they started to differentiate between 'L H' and 'L L' triplets in Sequence B, however, it was not modulated by the severity of the OC tendencies. Note that OC tendencies were treated as a continuous variable in our analyses, but for more illustrative data visualization, we exhibited results at Lower OC tendencies ($OCI-R = 14.24 - 11.73$, on the left) and Higher OC tendencies ($OCI-R = 14.24 + 11.73$, on the right) based on standard deviations from the mean. In all subfigures, points indicate means and error bars indicate SEM

structural changes in the task. Our results indicate that OC tendencies are not associated with individual differences in the resistance of predictive representations, as evidenced by the lack of significant interactions involving OCI-R scores in the analysis related to 'Old knowledge'. Similarly, we found no individual differences related to OC tendencies in the updating of predictive representations, as demonstrated by the results for 'New knowledge'. Overall, this suggests that the resistance and updating of predictive representations are not influenced by OC tendencies in the non-clinical population.

Discussion

In this study, we aimed to investigate potential individual differences in probabilistic learning and in updating predictive representations related to OC tendencies within the non-clinical population among university students. We implemented online experiments on two independent non-clinical samples ($N_{\text{Study1}} = 164$, $N_{\text{Study2}} = 256$), measuring OC tendencies as a continuous spectrum from the mildest prevalence to the highest. In Study 1, we focused on the implicit unsupervised acquisition of probabilistic contingencies, and our results indicated robust implicit probabilistic learning among OC tendencies. We took a step further in Study 2 by examining the ability to update predictive representations among OC tendencies. Our findings revealed that individuals with

elevated OC tendencies within a non-clinical population demonstrated superb updating capabilities of predictive representations. The results will be discussed here from three key perspectives: (I) the presence or absence of supervision, (II) the predictability of the information and (III) the level of awareness during the task.

Initially, theories posited that obsessions and compulsions continuously reinforce each other to obtain a rewarding sense of relief or avoid perceived consequences, even when perceived as irrational, they cannot control it [2]. This proposition was supported by the majority of studies demonstrating intact supervised learning in individuals with OCD [5, 7–11] but for exceptions see: [12, 13], showing that supervision makes learning efficient in OCD. Nevertheless, learning can occur also in the absence of supervision, and this form of learning has yielded mostly weaker results in OCD research to date [22–27], but for exceptions see: [28–30]. Consequently, our findings corroborate previous studies, indicating that non-clinical individuals with different levels of OC tendencies are also capable of learning effectively in an unsupervised context, just like individuals with clinical OCD [28–30]. This suggests that the issue lies not in the presence or absence of supervision, but in factors beyond that, as there are learning conditions in an unsupervised manner that can still be beneficial for them. One such factor that might influence the learning process is

the predictability of the information which could contribute to the complete implicitness of the process [19, 32]. Our results add to our understanding of the acquisition of more complex, probabilistic contingencies in relation to OC tendencies and clinical OCD, demonstrating robust performance akin to previous studies [9–11] but for exceptions see: [12, 13, 33]. Performance is also inconsistent when it comes to deterministic contingencies: easier associative patterns evoke efficient learning [5, 7] while fixed, repetitive first-order adjacent patterns (i.e., where one subsequently presented stimuli predict the upcoming one) evoke reduced performance [22–26] and intact performance in clinical OCD [8, 29, 30] and also among non-clinical OC tendencies [31, 33]. A recent study highlighted potential differences in performance under probabilistic versus deterministic conditions [33]. Building on this, we have demonstrated that individuals with non-clinical OC tendencies can efficiently acquire second-order probabilistic contingencies. However, further research is needed to elucidate the underlying factors influencing preferences for probabilistic or deterministic contingencies in both OCD and non-clinical OC populations.

Given that individuals with OCD, despite recognizing their actions as irrational, are unable to stop them, a third key factor influencing learning processes might be the explicit awareness during acquisition. In most studies, participants were explicitly informed that they were engaged in a learning process, and these studies mostly demonstrated intact performance [5, 7, 8, 26, 31]. In cases where participants were unaware that they were learning, studies have shown mixed results: some reported reduced performance [12, 13, 22–27], while others observed intact performance [9–11, 28–30]. Many of these studies have been criticized, as participants often acquired the tasks rapidly and efficiently, facilitating a transition from implicit to explicit learning [21, 26, 28]. In fact, in some cases, even superior explicit awareness was observed [22, 23]. Moreover, a study comparing explicit and implicit learning conditions found that individuals with OCD performed better when they had explicit knowledge of the learning process [26]. Our current findings, however, contradict this interpretation, as our participants were able to efficiently acquire information without any awareness of the learning process—similarly to a recent study where learning could also remain entirely implicit [28]. While this study did not directly assess the impact of task explicitness, the incorporation of second-order, non-adjacent dependencies within a noisy environment, along with the fact that participants were not informed they were in a learning condition, effectively maintained the task as entirely implicit [19, 32]. Future research is therefore needed to pinpoint the

effect of explicit instructions on probabilistic contingencies, expanding on those applied to deterministic ones.

Beyond the implicit extraction of probabilistic contingencies, our study advances our knowledge by focusing on the updating of predictive representations among OC tendencies. Our results do not align with prior theories since the incidental updating of predictive representations remained superb among OC tendencies in a non-clinical population. Prominent theories of OCD highlight both an excessive bias toward well-established knowledge [5, 7, 8] and also difficulties in relying on previous knowledge [33, 34]. The inconsistency between our results and the previous theories may stem from the fact that they measured supervised learning processes, in which reward-associated behaviour persisted for participants even after it had been devalued or diminished following explicit prior warnings [5, 7, 8]. In our study, we did not provide warnings, hence, participants were unaware they are in a learning situation, and that the stimulus sequence structure changed during the task (from sequence A to sequence B and back to sequence A). This allowed us to capture a much more implicit, warning-free, and non-reward driven updating mechanism. Interestingly, our results do not align with the theory suggesting that individuals with subclinical OC tendencies rely less on past experiences and prefer recent outcomes [33, 34], as they showed superb updating capabilities regarding both past experiences (Old knowledge) and novel one (New knowledge). The theory was based on more explicit processes and the task did not involve excessive training necessary for the development of stable predictive representations [33]. It was also posited that individuals face greater difficulties under probabilistic contingencies, leading to increased uncertainty and exploratory behaviour compared to deterministic conditions [33]. Similarly, previous research has also demonstrated that in deterministic situations, explicit awareness can enhance performance in individuals with OCD [26], whereas they experienced difficulties in the probabilistic condition, which contradicts our findings. This discrepancy could be explained, for instance, by the extended exposure to repetitive probabilistic patterns which may have helped participants overcome uncertainty and enabled the efficient updating of predictive representations without requiring explicit awareness. In summary, existing theories on updating mechanisms in OCD suggest both a bias toward relying on past information and a reduced ability to effectively utilize it. Our approach offers a new perspective, and complements these two, by showing that individuals with subclinical OC tendencies can adapt to new situations without prior warning, while also retaining and incorporating new information. This study has outlined the learning and updating mechanisms while acknowledging that the maladaptive behavioural manifestations of OCD

and OC tendencies can be shaped by the complex interplay of neurocognitive processes, specifically, between goal-directed and habitual (automatic) processes [3, 5, 7, 8, 57–59]. Goal-directed systems encompass cognitive control functions to support adaptive behaviour, regulate the achievement of desired goals, and the avoidance of undesired consequences [60, 61]. Although this theory is primarily based on a supervised, associative learning paradigm [5, 7, 8], it remains essential for interpreting our findings, as probabilistic learning also captures habitual processes, directly addressing a core aspect of habit formation [19]. Hence, our results align with these findings, showing that probabilistic (or habitual) learning remained robust along the spectrum of subclinical OC tendencies in an unsupervised manner. At the same time, a theory based on probabilistic learning also emphasizes a dynamic interplay, highlighting the competitive relationship between habitual processes and the prefrontal cortex and its inherent goal-directed control processes [19, 62–65]. Even though this study did not focus directly on the interplay between neurocognitive processes, our findings on robust probabilistic learning lay the groundwork for bridging these two previously distinct research lines. To achieve this, future research is highly warranted to unravel how the interplay or imbalance between probabilistic learning and goal-directed control processes contributes to the behavioural manifestations of both clinical OCD and non-clinical OC tendencies.

To the best of our knowledge, this is the first study to empirically test the unsupervised acquisition of probabilistic second-order non-adjacent dependencies and the updating of predictive representations among OC tendencies in the non-clinical population. It went beyond the traditional dichotomous comparison between clinical and neurotypical groups. The major issue with dichotomous group comparisons is that OCD is a heterogeneous condition [66–70], with varying cognitive profiles also related to statistical learning [23, 29]. Examining a broad spectrum of individuals from the non-clinical population with OC tendencies enables a more nuanced analysis. However, as a consequence, it remains uncertain whether there are qualitative differences between clinical and non-clinical populations. Following the example of Hoven et al. [15]’s metacognition study, researchers should next compare probabilistic learning in individuals diagnosed with OCD and undiagnosed individuals who exhibit similar levels of OC tendencies.

This study’s limitations must be considered when interpreting the results. First, both experiments were conducted online using convenience sampling in a cross-sectional design. As a result, we were only able to recruit a subset of the non-clinical population—primarily young adults. Furthermore, this study focused exclusively on the role of subclinical OC tendencies in probabilistic learning

and the updating of predictive representations without accounting for other potentially confounding psychiatric traits such as anxiety and depression, which are closely linked to OC tendencies [4, 71, 72]. As a result, the specificity of our findings remains somewhat limited, highlighting the need for larger-scale studies to further investigate these relationships. However, the robustness of our findings is enhanced by both the wide variability in OC tendencies observed across our samples and the acceptable psychometric properties of the ASRT task [40]. Additionally, we applied trial-by-trial-based (generalized) linear mixed models, which provide greater flexibility in handling distributional assumptions (such as the spectrum view considered here) and managing confounding variables [52, 73–75]. In the long run, to further strengthen our findings, it would be beneficial to replicate the current measurements using other probabilistic learning paradigms. Moreover, to more effectively identify individual differences and address reliability concerns associated with cross-sectional designs, the implementation of longitudinal designs is necessary [73, 74].

In summary, our study revealed robust probabilistic learning and superb updating capabilities of predictive representations associated with individual differences in OC tendencies in two non-clinical samples. Our results may provide a new direction for existing theories on implicit information processing in OCD and also among OC tendencies. Further multiprocess studies not only could contribute to a better understanding of OCD but could also enable the development of individualized prevention and therapeutic approaches. Probabilistic learning might assist in forming and maintaining new skills and habits in psychotherapy. If this form of learning remains intact in OCD, we can build upon it to develop new procedures, including skill-based therapies, such as reading or music-based interventions. Another potential approach is the intentional incorporation of noise or probabilistic variability into processes. Such interventions aim to help individuals break free from compulsive behaviours by exposing them to uncertainty and enabling them to learn to accept it without resorting to ritualistic actions. In conclusion, those who repeatedly check whether they have locked the front door or doubt that their wallet and phone are in their bag or pockets are still capable of extracting probability-based information from environmental cues and of properly predicting future events.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12888-025-06786-4>.

Supplementary Material 1

Supplementary Material 2

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Author contributions

B. B.: Conceptualization, Software, Validation, Investigation, Data Curation, Formal analysis, Writing – Original Draft, Writing – Review & Editing, Visualization; B. C. F.: Methodology, Software, Validation, Formal analysis, Writing – Review & Editing, Visualization; F. H.: Data Curation, Formal analysis, Writing – Review & Editing; O. P.: Writing – Review & Editing; E. T-F.: Writing – Review & Editing; K.F.: Writing – Review & Editing, Funding; K.C.: Writing – Review & Editing; D.N.: Conceptualization, Software, Validation, Resources, Writing – Review & Editing, Supervision, Funding; T.V.: Conceptualization, Software, Validation, Investigation, Data Curation, Formal analysis, Resources, Writing – Review & Editing, Supervision. All authors reviewed the manuscript.

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Data availability

The data and analysis codes are available at the OSF repository (<https://osf.io/fae2z/>).

Declarations

Ethics approval and consent to participate

Both studies obtained approval from the Research Ethics Committee of Eötvös Loránd University Budapest, Hungary (2021/504), under the principles of the Declaration of Helsinki. Participants provided their informed consent to participate in the study.

Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT 3.5 to improve the writing style of our proposal. The author(s) reject using AI for scientific purposes to gain unethical benefits. However, the author(s) believe that it helps the equality of native and non-native English speakers to have the same opportunities. Thus, the author(s) do recommend using generative AI for lingual purposes (only). After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Competing interests

The authors declare no competing interests.

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5. Study 3: How do non-clinical OC tendencies modulate the dynamic interplay between statistical learning and cognitive flexibility?

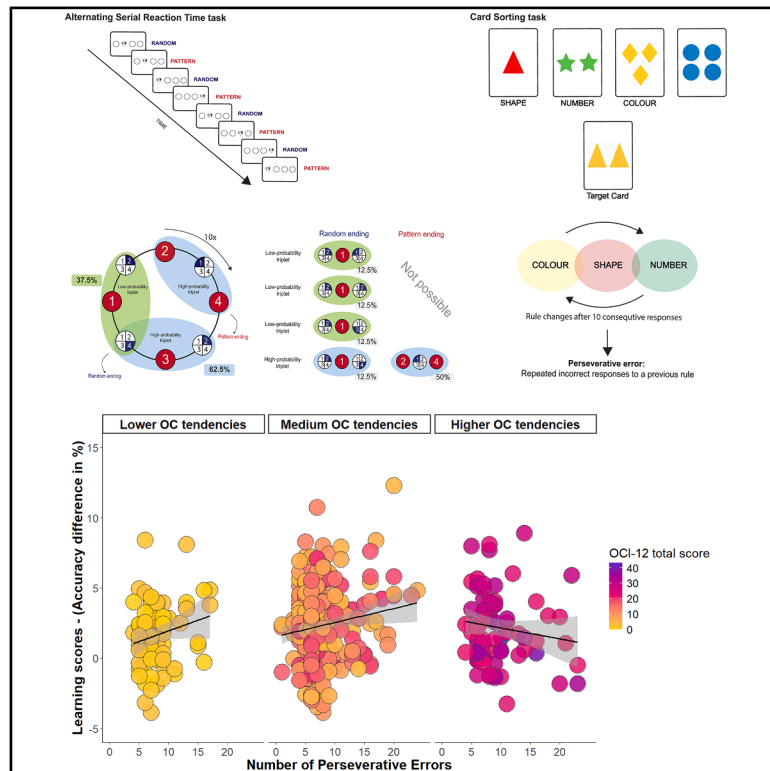
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Obsessive-compulsive tendencies shift the balance between competitive neurocognitive functions

Graphical abstract



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In brief

Health sciences; Medicine; Medical specialty; Psychiatry; Natural sciences; Biological sciences; Neuroscience; Cognitive neuroscience

Highlights

- OCD theories propose an imbalance between automatic and goal-directed control
- We show the first evidence of this imbalance via an unsupervised learning paradigm
- Statistical learning and cognitive flexibility showed an antagonistic relationship
- Crucially, this antagonistic pattern weakened with increasing OC tendencies



Article

Obsessive-compulsive tendencies shift the balance between competitive neurocognitive functions

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SUMMARY

Obsessive-compulsive disorder (OCD) has been theorized to reflect an imbalance between automatic and goal-directed processes. However, evidence for this imbalance has relied almost exclusively on reward- and feedback-based paradigms, leaving unsupervised learning mechanisms largely unexplored. We investigated this imbalance by examining the relationship between statistical learning (SL) - a feedback-free, implicit mechanism for detecting environmental regularities - and cognitive flexibility, the ability to adapt behavior to changing demands. Adopting a spectrum approach to obsessive-compulsive (OC) tendencies, a total of 404 university students completed an online probabilistic sequence learning task and a card-sorting task. Results revealed an antagonistic relationship between SL and cognitive flexibility, such that stronger SL was associated with lower cognitive flexibility. Crucially, this inverse association weakened with increasing OC tendencies. These findings provide the first evidence that OC tendencies alter the interplay between automatic and goal-directed functions in a purely unsupervised learning context, extending current theoretical frameworks beyond supervised and reward-dependent paradigms.

INTRODUCTION

A core challenge in human cognition involves maintaining a dynamic interplay between efficient automatic and flexible goal-directed functions to support adaptive behavior. Goal-directed behavior relies on a broad set of executive functions - including cognitive flexibility, inhibitory control, and working memory updating - that support the attainment of desired outcomes and the avoidance of undesired ones.¹⁻³ In contrast, automatic behavior depends on previously acquired associations and operates with reduced conscious engagement.⁴⁻⁶ Disruption of this interplay can lead to behavioral difficulties, as seen in conditions such as obsessive-compulsive disorder (OCD), where automaticity tends to dominate over goal-directed control, resulting in rigid, repetitive mental (obsessions) and behavioral rituals (compulsions).⁷⁻¹³ Indeed, varying degrees of obsessions and compulsive acts, collectively referred to as obsessive-compulsive (OC) tendencies, are distributed along a continuum

in the general population and, when persistent and sufficiently severe, culminate in a clinical presentation of OCD.¹⁴⁻²² Considering OC tendencies on a dimensional continuum provides a more precise and comprehensive identification of the neurocognitive mechanisms underlying OCD, effectively overcoming the limitations of traditional categorical diagnoses that often obscure the continuous and nuanced variability of these symptoms.^{9,14,23-25} Therefore, the present study aimed to delineate the role of the balance between automatic and goal-directed functions underlying maladaptive behaviors of OCD by assessing OC tendencies as a dimensional spectrum within the non-clinical university student population.

Prominent theoretical models propose that the repetitive symptoms of OCD and transdiagnostic tendencies arise from diminished goal-directed control coupled with a corresponding dominance of habitual responding.^{10-13,26-28} Evidence for this framework has been driven largely by dual-task paradigms, which show that increasing cognitive demands can bias the



expression of these processes within a given task.^{10–13,26–28} While these findings establish that controlled and automatized systems interact in a demand-sensitive manner, they are inherently constrained to within-task dynamics, leaving unresolved whether comparable patterns extend across tasks that differentially engage these processes. These approaches do not clearly distinguish between competing mechanistic accounts of this shift, whether it reflects increased reliance on habitual processes, reduced goal-directed control, or a disruption in the coordination between the two. Moreover, it remains unclear whether these imbalances are consistent across tasks or whether they primarily reflect context-dependent performance constraints within specific paradigms rather than more stable individual differences. The present study addresses this question by testing whether inter-individual variability in performance is systematically aligned across paradigms that place distinct demands on controlled and automatized processing, and whether such alignment relates to OC tendencies. By shifting the focus from within-task modulation to cross-task structure, this approach offers a complementary perspective on how variability in cognitive performance is organized across individuals, thereby refining current accounts of the mechanisms implicated in compulsivity. From a habitual perspective, a key limitation of current frameworks becomes apparent. Evidence from outcome devaluation and related supervision-based paradigms consistently points to enhanced habitual responding in OCD and compulsivity.^{12,13,29} Yet in these tasks, the balance between goal-directed and habitual control is tightly coupled to continuous external reward or feedback, making it difficult to isolate learning mechanisms from reward-driven performance. Consequently, understanding OC requires moving beyond feedback-dependent paradigms to probe the underlying, feedback-independent mechanisms.²⁰ Addressing this question requires considering recent advances in learning theory, which emphasize the crucial role of unsupervised processes in driving neural plasticity and establishing the foundation for supervised learning.³⁰ From this perspective, supervised learning emerges as a later process built upon earlier, reward-free, unsupervised mechanisms.³⁰ Accordingly, to better understand the development and persistence of automatic, compulsive behavioral characteristics of OCD and OC tendencies, it is essential to disentangle feedback sensitivity and pure learning mechanisms²⁰ and to revisit the primary role of unsupervised learning and its interaction with prefrontal cortex-related functions.

One such unsupervised learning mechanism is statistical learning (SL), a fundamental function that supports the acquisition of skills and habits through the incidental extraction of novel probabilistic patterns from the environmental stream.^{31–34} SL in clinical OCD populations has shown both reduced and intact results (for review, see: Brezóczi et al.³⁵), while individuals scoring on the dimensional OC scale demonstrate intact or even faster learning rates.²⁰ This highlights the need to better understand how other neurocognitive functions contribute to such performance. Indeed, within the framework of interactive memory systems, neurocognitive functions such as SL rarely operate in isolation; instead, they engage in dynamic and often competitive interactions with goal-directed functions.^{6,36,37} Typically, increased reliance on one system corresponds with the reduced

engagement of the other, as demonstrated by the inverse relationship between SL and goal-directed functions. In this context, cognitive flexibility, defined as the capacity to shift behavior, strategies, or mental frameworks in response to changing environmental demands, is a particularly critical goal-directed function,^{1–3} and maladaptive, rigid, and repetitive behavioral patterns of OC may reflect its impairments.^{38,39} If OCD and OC tendencies are associated with a disruption in the balance between automatic and goal-directed functions, then investigating their interaction outside the influence of supervision becomes particularly informative.

To provide a complementary perspective on the neurocognitive profile underlying OCD and OC tendencies, this study focused on SL and goal-directed function, specifically cognitive flexibility. Therefore, in the present study, we recruited 404 adult participants from university courses for an online experiment. SL was assessed using an unsupervised learning paradigm, the Alternating Serial Reaction Time (ASRT) task,^{40,41} which is a probabilistic learning task that lacks supervision and reinforcement-based factors on SL performance (Figure 1). Cognitive flexibility was operationalized as the number of perseverative errors on the card sorting task (CST),⁴² a widely accepted and extensively used measure of cognitive flexibility (Figure 1).^{43–46} OC tendencies were assessed dimensionally using the obsessive-compulsive inventory, OCI-12 questionnaire.⁴⁷ The present study aimed to uncover the interplay between SL and cognitive flexibility and to investigate the individual differences in their interaction among university students scoring on the dimensional OC measure. Based on existing literature, we hypothesized an antagonistic relationship between SL and cognitive flexibility, such that stronger performance on the ASRT task would be associated with weaker performance on the CST. Crucially, we further hypothesized that OC tendencies would modulate this interaction, with the relationship between SL and cognitive flexibility varying across different levels of OC tendencies and potentially diverging from a straightforward competitive pattern at higher levels of OC tendencies.

RESULTS

How do OC tendencies modulate the interplay between cognitive flexibility and statistical learning?—Reaction time

We performed a linear mixed-effects model on blockwise median RT of the ASRT task, with fixed effects for Time (Blocks 1–15), Triplet Type (high-vs. low-probability), OCI-12 score, number of Perseverative Errors of the CST, and all higher-order interactions. Random effects included participant-specific intercepts and a random slope for Time to account for individual variability. The statistical parameters underlying the effects reported above are summarized in Table 1, whereas the full set of statistical estimates (b, SE, 95% CI, t, df, and p values) is provided in Table S1.

The model reported a statistically significant main effect of Triplet Type in the ASRT task, indicating faster RTs for high-probability trials compared to low-probability trials, which evidences statistical learning during the task. The main effect of Time indicated a decrease in RTs throughout the task, demonstrating changes in visuomotor performance over time.

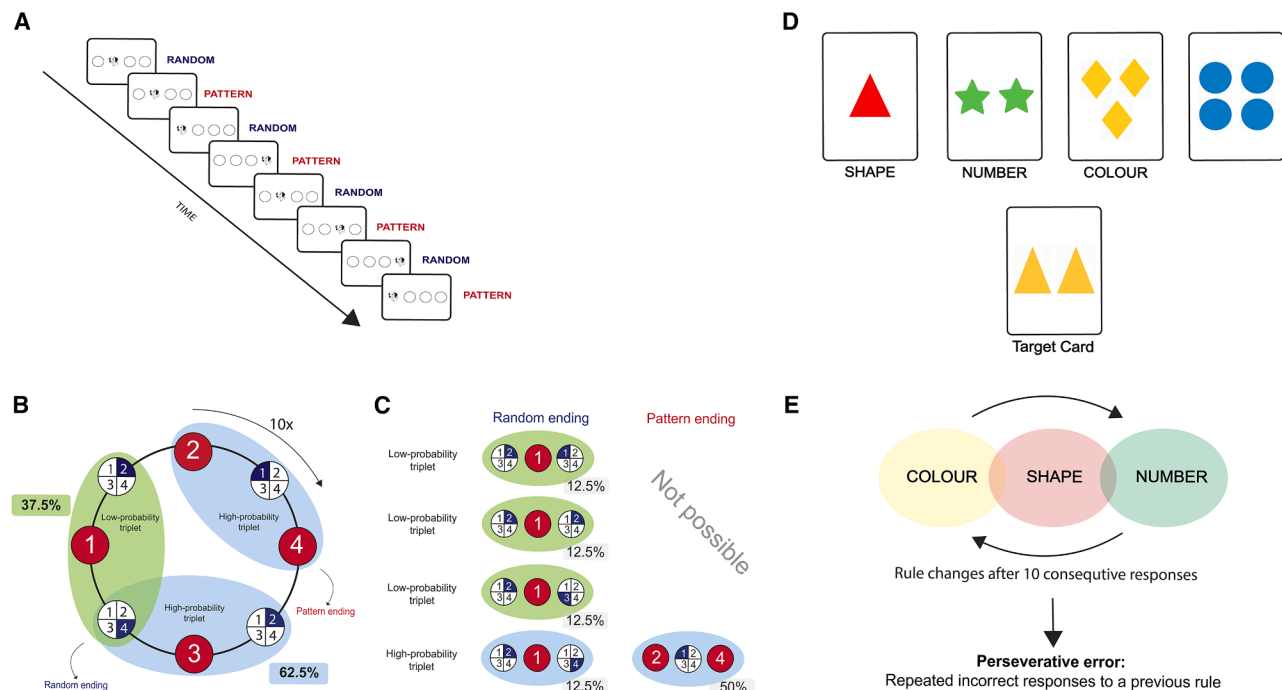


Figure 1. Design of the Study

(A) In the Alternating Serial Reaction Time (ASRT) task, participants were instructed to respond by pressing keys corresponding to the spatial location of a target stimulus, depicted as a dog's head. Each trial followed an eight-element probabilistic sequence composed of alternating pattern and random elements. For example, a sequence such as 2–r–4–r–3–r–1–r consisted of fixed pattern trials at positions 2, 4, 3, and 1 (from left to right), interleaved with random elements, denoted by “r,” which could appear at any of the four possible locations.

(B) Each trial was considered the third element in a sequence of three consecutive trials (a triplet). Pattern elements, which consistently appeared in fixed positions throughout the task, were displayed with red backgrounds, whereas random elements, selected randomly from the four possible locations, were shown with blue backgrounds. The structure of the sequence resulted in certain triplets occurring more frequently than others. These were categorized as high-probability triplets, while less frequent combinations were defined as low-probability triplets.

(C) For illustrative purposes, three triplets are highlighted: 2(P)–1(R)–4(P), a pattern-ending high-probability triplet; 2(R)–3(P)–4(R), a random-ending high-probability triplet; and 4(R)–1(P)–2(R), a random-ending low-probability triplet. High-probability triplets could occur in one of the two ways: either with two pattern trials and a random trial in the middle (accounting for 50% of all trials), or with two random trials and a pattern trial in the middle (accounting for 12.5% of trials). Overall, 62.5% of trials constituted the final element of a high-probability triplet, whereas the remaining 37.5% served as the final element of a low-probability triplet.

(D) Schematic illustration of the Card Sorting Task (CST). Four reference cards are presented simultaneously, differing along three stimulus dimensions (color, shape, and quantity). On each trial, a target card appears below the reference cards, and participants are instructed to match it to one of the reference cards according to a sorting rule.

(E) The rules are presented in a fixed, repeating order for up to six categories: color, shape, number. The sorting rule changes after ten consecutive correct responses. Cognitive flexibility is indexed by the number of perseverative errors, defined as continued application of a previously correct but currently invalid rule.

Importantly, the interaction between Triplet Type and time suggested that statistical learning developed gradually, as the difference between high- and low-probability trials increased over time.

Cognitive flexibility was significantly associated with overall RT performance, as reflected by a main effect of Perseverative Error on the CST, whereby a higher number of perseverative errors, indicative of reduced cognitive flexibility, predicted slower responses. However, the absence of statistically significant interactions involving Perseverative Error suggests that cognitive flexibility did not modulate visuomotor performance (Time $\times$ Perseverative Error), statistical learning (Triplet Type $\times$ Perseverative Error), or the trajectory of statistical learning (Time $\times$ Triplet Type $\times$ Perseverative Error).

In contrast, OCI-12 scores showed no statistically significant main effect and did not interact with any of the task-related vari-

ables, indicating that OC tendencies were not significantly associated with baseline RT (main effect of OCI-12 score), cognitive flexibility (OCI-12 score $\times$ Perseverative Error), visuomotor performance (Time $\times$ OCI-12 score), statistical learning (Triplet Type $\times$ OCI-12 score), the trajectory of statistical learning (Time $\times$ Triplet Type $\times$ OCI-12 score). Moreover, OCI-12 scores did not modulate the relationship between cognitive flexibility (Perseverative Error $\times$ Triplet Type $\times$ OCI-12 score, see Figure 2) and the dynamics of statistical learning in the present study (Perseverative Error $\times$ Time $\times$ Triplet Type $\times$ OCI-12 score).

How do OC tendencies modulate the interplay between cognitive flexibility and statistical learning?—Accuracy

We performed a linear mixed-effects model on blockwise mean accuracy of the ASRT task, with fixed effects for time (Block

Table 1. Results of the linear mixed-effects model predicting blockwise median reaction time

Effect	df	F	p
Time	1, 399.98	125.06	< 0.001
Triplet Type	1, 11297.07	169.21	< 0.001
OCI-12 score	1, 400.01	3.15	0.077
Perseverative Error	1, 400.02	7.31	0.007
Time × Triplet Type	1, 11297.10	10.42	0.001
Time × OCI-12 score	1, 399.88	0.15	0.699
Triplet Type × OCI-12 score	1, 11297.11	0.00	0.926
Time × Perseverative Error	1, 400.07	3.13	0.078
Triplet type × Perseverative Error	1, 11297.07	0.44	0.508
OCI-12 score × Perseverative Error	1, 400.01	0.26	0.600
Time × Triplet Type × OCI-12 score	1, 11297.18	0.09	0.763
Time × Triplet Type × Perseverative Error	1, 11297.1	0.92	0.338
Time × OCI-12 score × Perseverative Error	1, 400.00	3.61	0.058
Triplet Type × OCI-12 score × Perseverative Error	1, 11297.09	1.29	0.257
Time × Triplet Type × OCI-12 score × Perseverative Error	1, 11297.15	0.67	0.412

The table summarizes all main effects and interactions. Degrees of freedom (df) correspond to Satterthwaite approximations. *F* = *F*-statistic; *p* = significance value. Statistically significant results (*p* < 0.05) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type (high vs. low) was significant (*b* = −5.87, SE = 0.45, *z* = −13.01, *p* < 0.001, 95% CI [−6.76, −4.99]), indicating faster responses to high- than to low-probability triplets. Time was also significant (*b* = −1.1, SE = 0.10, *z* = −11.18, *p* < 0.001, 95% CI [−1.29, −0.9]), showing that RT decreased as the task progressed. Statistically significant main effect of Perseverative Error indicated that more perseverative errors were associated with slower reaction times (*b* = 1.44, SE = 0.53, *z* = 2.70, *p* = 0.007, 95% CI [0.4, 2.49]). The significant Time × Triplet Type interaction (*b* = −0.34, SE = 0.10, *z* = −3.23, *p* = 0.001, 95% CI [−0.54, −0.13]) reflected gradual improvement in statistical learning over time. Time was treated as a continuous variable in all analyses; however, for the post hoc analyses, it was segmented into three time points (Block₅, Block₁₀, Block₁₅). Block₅ (*b* = −4.86, SE = 0.55, *z* = −8.84, *p* < 0.001, 95% CI [−5.94, −3.78]), Block₁₀ (*b* = −6.55, SE = 0.50, *z* = −13.16, *p* < 0.001, 95% CI [−7.52, −5.57]), and Block₁₅ (*b* = −8.24, SE = 0.86, *z* = −9.58, *p* < 0.001, 95% CI [−9.92, −6.55]). Sidak-adjusted pairwise comparisons revealed significant differences in statistical learning (High vs. Low differences) between Block₅–Block₁₀ (*b* = 1.69, SE = 0.52, *z* = 3.23, *p* = 0.004), Block₅–Block₁₅ (*b* = 3.37, SE = 1.05, *z* = 3.23, *p* = 0.004), and Block₁₀–Block₁₅ (*b* = 1.69, SE = 0.52, *z* = 3.23, *p* = 0.004).

1–15), Triplet Type (high-vs. low-probability), OCI-12 score, number of Perseverative Errors of the CST, and all higher-order interactions. Random effects included participant-specific intercepts and correlated slopes for Time and Triplet Type to account for individual variability. The statistical parameters underlying the effects reported above are summarized in Table 2, whereas the full set of statistical estimates (*b*, SE, 95% CI, *t*, *df*, and *p* values) is provided in Table S2.

Participants were more accurate on high-probability trials than on low-probability trials, providing clear evidence of statistical learning (main effect of Triplet Type). Overall accuracy declined slightly over the course of the ASRT task (main effect of Time), but the difference between high- and low-probability trials increased, indicating a gradual improvement in statistical learning (Time × Triplet Type) on the ASRT task.

Cognitive flexibility influenced performance: A higher number of perseverative errors on CST was significantly associated with lower overall accuracy (main effect of Perseverative Error), and a modest decline in visuospatial performance over time on the ASRT task (Time × Perseverative Error). Moreover, a significant Triplet Type × Perseverative Error interaction revealed an antagonistic relationship between statistical learning and cognitive flexibility (Triplet Type × Perseverative Error), with greater statistical learning linked to reduced cognitive flexibility, that is higher number of perseverative errors: (*b*_{Low perseverative errors} = 1.95, 95% CI [1.59, 2.30]; *b*_{Mean perseverative errors} = 2.22, 95%

CI [1.97, 2.47]; *b*_{High perseverative errors} = 2.50, 95% CI [2.13, 2.86]). Pairwise comparisons indicated that the statistical learning increased significantly with perseverative errors (*b*_{Low perseverative errors} − Mean perseverative errors = −0.28, 95% CI [−0.53, −0.02], *p* = 0.034; *b*_{Low perseverative errors} − High perseverative errors = −0.55, 95% CI [−1.06, −0.04], *p* = 0.034; *b*_{Mean perseverative errors} − High perseverative errors = −0.28, 95% CI [−0.53, −0.02], *p* = 0.034). Thus, individuals with poorer cognitive flexibility (higher numbers of perseverative errors) exhibited enhanced statistical learning, except when considering the trajectory of learning (Time × Triplet Type × Perseverative Error), where this pattern was less pronounced.

OC tendencies did not significantly influence overall accuracy (main effect of OCI-12 score), visuospatial performance (Time × OCI-12 score), statistical learning (Triplet Type × OCI-12 score), or its improvement over time (Time × Triplet Type × OCI-12 score). Similarly, no interactions were observed between OC tendencies and perseverative errors for overall accuracy or visuospatial performance (Time × Perseverative Error × OCI-12 score). However, a significant Triplet Type × Perseverative Error × OCI-12 score interaction indicated that OC tendencies modulate the antagonistic relationship between statistical learning and cognitive flexibility (see Figure 3). The post hoc analysis examining the trend of statistical learning across perseverative error levels (M-SD, M, M + SD) revealed that among individuals with lower OC tendencies, perseverative errors on CST were positively associated

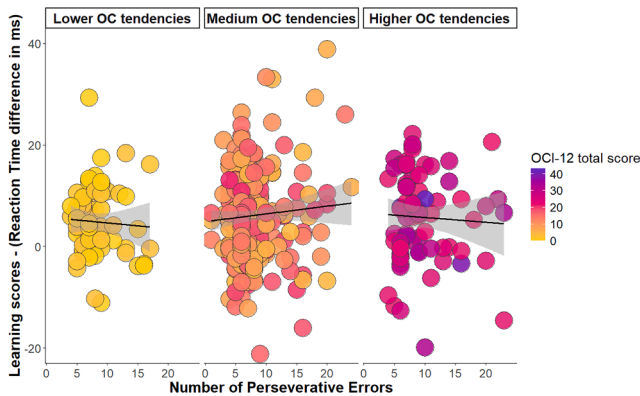


Figure 2. Relationship between cognitive flexibility and reaction time-based statistical learning across OCI-12 scores

The figure illustrates the relationship between cognitive flexibility, as measured by the number of perseverative errors on the card sorting task along the x axis, and statistical learning performance along the y axis, which is operationalized as the difference in reaction time between high- and low-probability triplets. Each point represents an individual participant, with color encoding their total OCI-12 score along a continuous gradient from low (yellow) through intermediate (pink) to high (purple) obsessive-compulsive tendencies. A linear regression line with 95% confidence intervals is overlaid in black. While the OCI-12 score was treated as a continuous variable in all statistical analyses, for visualization purposes, the data are faceted by the levels of OC tendencies. These levels represent varying degrees of OCI-12 scores, approximating one standard deviation below the mean (lower OC tendencies), at the mean (medium OC tendencies), and one standard deviation above the mean (higher OC tendencies), respectively. The color gradient used in the plot (yellow to pink to purple) visually reflects this increase in the level of OC tendencies. No relationship was observed between cognitive flexibility and RT-based statistical learning, and this pattern was consistent across levels of OC tendencies.

with statistical learning, with a significant slope ($b = 0.145$, $SE = 0.048$, $z = 2.97$, 95% CI [0.050, 0.242], $p = 0.002$). A similar but weaker positive relationship was observed at the medium level of OC tendencies ($b = 0.069$, $SE = 0.032$, $z = 2.11$, 95% CI [0.005, 0.134], $p = 0.034$), suggesting that poorer cognitive flexibility was linked to enhanced statistical learning among lower and medium levels of OC tendencies. In contrast, this association disappeared among individuals with higher OC tendencies, where the slope was not statistically significant ($b = -0.006$, $SE = 0.040$, $z = -0.17$, 95% CI [-0.086, 0.072], $p = 0.862$). These coefficients indicate effects of modest magnitude and should be interpreted as reflecting relatively small differences between conditions. Overall, statistical learning increased as the number of perseverative errors rose for individuals with lower to medium OC tendencies, reflecting an antagonistic pattern in which reduced cognitive flexibility was accompanied by better statistical learning. This antagonistic pattern weakened in participants with high OC tendencies, where statistical learning remained moderate regardless of cognitive flexibility. Importantly, this modulation was not observed when examining the full trajectory of learning over time (Triplet Type $\times$ Time $\times$ Perseverative Error $\times$ OCI-12 score).

DISCUSSION

In this study, we addressed a critical gap in understanding the relationship between goal-directed and automatic behavior by

examining how unsupervised SL interacts with cognitive flexibility across individuals. Rather than focusing on within-task dynamics, we tested whether this relationship generalizes across functions and is systematically modulated by OC tendencies. We conducted an online experiment in a non-clinical university sample, assessing OC tendencies dimensionally across a continuous spectrum. SL was evaluated using an unsupervised learning task, while cognitive flexibility was assessed with the CST. Our findings corroborate previous theories indicating a competitive interaction between SL and executive functions, specifically cognitive flexibility. Importantly, this relationship was not consistent across individuals: The inverse association between SL and cognitive flexibility weakened as OC tendencies increased. This pattern suggests that variability in OC tendencies fundamentally alters how automatic and controlled processes interact across tasks, rather than reflecting a simple shift in the dominance of one system over the other.

Our results build upon existing theories that highlight a disruption between automatic and goal-directed processes in both clinical OCD and OC tendencies or compulsivity.^{9–13,23,29} In particular, the typical antagonistic relationship between these functions, as emphasized by competitive memory system frameworks^{6,36,37,48} appears to weaken with the increase of OC tendencies. This pattern may appear to challenge the habit hypothesis,^{10–12,27,49} which posits a shift toward habitual control under conditions of impaired goal-directed processing. However, methodological differences may partly account for these discrepancies since they predominantly rely on within-task paradigms, such as outcome devaluation or contingency degradation, which assess goal-directed behavior through adaptation to altered contingencies following extended instrumental training within a single context.^{10–12} Such paradigms often require the coordination of multiple processes simultaneously, and therefore capture how performance shifts under increased task demands. By contrast, the present findings point to a different form of alteration: The individual functions themselves remain largely intact, but their interaction changes with the increase of OC tendencies. Specifically, at lower levels of OC tendencies, SL and cognitive flexibility exhibit the expected antagonistic interplay, consistent with competitive memory frameworks.^{6,36} As OC tendencies increase, however, this relationship progressively diminishes, indicating that these processes no longer effectively constrain or inform one another. Importantly, this pattern does not reflect a simple shift in dominance, whereby one system overrides the other. Rather, it suggests a breakdown in their coordinated interaction, such that automatic and controlled processes operate more independently, without the typical antagonistic modulation. From this perspective, OC tendencies may be better characterized by altered coordination between cognitive systems than by dysfunction within any single function.

Taken together, the present results indicate that increasing OC tendencies are associated with a weakening of the relationship between executive control and SL. Importantly, the current design allowed for the independent assessment of these functions, enabling us to characterize not only their individual integrity but also their interaction. This distinction is critical for disentangling whether maladaptive behavioral patterns arise from

Table 2. Results of the linear mixed-effects model predicting blockwise mean accuracy

Effect	df	F	p
Time	1, 400.22	58.82	< 0.001
Triplet Type	1, 400.14	302.7	< 0.001
OCI-12 score	1, 399.97	0.00	0.976
Perseverative Error	1, 400.06	6.18	0.013
Time × Triplet Type	1, 10898.51	33.15	< 0.001
Time × OCI-12 score	1, 400.05	0.01	0.935
Triplet Type × OCI-12 score	1, 399.91	0.89	0.347
Time × Perseverative Error	1, 400.39	4.41	0.036
Triplet Type × Perseverative Error	1, 400.52	4.48	0.035
OCI-12 score × Perseverative Error	1, 400.03	0.91	0.341
Time × Triplet Type × OCI-12 score	1, 10898.03	0.98	0.321
Time × Triplet Type × Perseverative Error	1, 10899.01	0.04	0.845
Time × OCI-12 score × Perseverative Error	1, 400.26	2.30	0.130
Triplet Type × OCI-12 score × Perseverative Error	1, 400.30	6.21	0.013
Time × Triplet Type × OCI-12 score × Perseverative Error	1, 10898.65	1.81	0.178

The table summarizes all main effects and interactions. Degrees of freedom (df) correspond to Satterthwaite approximations. F = F-statistic; p = significance value. Statistically significant results ($p < 0.05$) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type indicated higher accuracy for high- than for low-probability triplets ($b = 2.22$, $SE = 0.13$, $z = 17.40$, $p < 0.001$, 95% CI [1.97, 2.47]). Time was also significant ($b = -0.15$, $SE = 0.02$, $z = -7.67$, $p < 0.001$, 95% CI [-0.18, -0.11]), showing that accuracy decreased as the task progressed. The main effect of Perseverative Error indicated that more perseverative errors were associated with lower accuracy ($b = -0.11$, $SE = 0.04$, $z = -2.49$, $p = 0.013$, 95% CI [-0.2, -0.02]). Time × Triplet Type interaction revealed improvement in statistical learning over time. Time was treated as a continuous variable in all analyses; however, for the post hoc analyses, it was segmented into three time points (Block₅, Block₁₀, Block₁₅). Block₅ ($b = 1.75$, $SE = 0.15$, $z = 11.56$, $p < 0.001$, 95% CI [1.46, 2.05]), Block₁₀ ($b = 2.54$, $SE = 0.14$, $z = 18.26$, $p < 0.001$, 95% CI [2.26, 2.81]), and Block₁₅ ($b = 3.32$, $SE = 0.23$, $z = 14.48$, $p < 0.001$, 95% CI [2.87, 3.77]). Sidak-adjusted pairwise comparisons revealed significant differences between Block₅–Block₁₀ ($b = -0.78$, $SE = 0.14$, $z = -5.76$, $p < 0.001$), Block₅–Block₁₅ ($b = -1.57$, $SE = 0.27$, $z = -5.76$, $p < 0.001$), and Block₁₀–Block₁₅ ($b = -0.78$, $SE = 0.14$, $z = -5.76$, $p < 0.001$). For the Time × Perseverative Error interaction, Sidak-adjusted pairwise comparisons showed significant declines over time at lower perseverative error levels ($b = -0.11$, $SE = 0.03$, $z = -3.92$, $p < 0.001$, 95% CI [-0.16, -0.05]; at mean: $b = -0.15$, $SE = 0.02$, $z = -7.67$, $p < 0.001$, 95% CI [-0.18, -0.11]) and at higher perseverative error levels ($b = -0.19$, $SE = 0.03$, $z = -6.79$, $p < 0.001$, 95% CI [-0.24, -0.13]), indicating a decline in visuomotor performance over time. Perseverative Error was treated as a continuous variable in all primary analyses; however, for the post hoc analyses, it was depicted in three categories (M–SD, M, M + SD).

enhanced automaticity,^{28,50,51} reduced goal-directed control,⁹ or alterations in the coordination between these systems.⁵² This perspective aligns with recent interaction-based accounts, which emphasize that cognitive inflexibility and habitual behavior act as independent yet interacting predictors of OC symptomatology.¹⁹ Notably, prior work has demonstrated that these processes exert a compensatory interaction, such that both heightened habitual tendencies and reduced flexibility are jointly required for elevated symptom expression, while neither is sufficient in isolation.¹⁹ At the same time, meta-analytic evidence challenges the assumption that executive or goal-directed functions are independently impaired in OCD, suggesting that observed deficits may reflect broader performance-related factors rather than specific functional dysfunctions.⁵³ In this context, our findings provide a complementary perspective: Rather than reflecting deficits within individual systems, increasing OC tendencies are associated with a disruption in the functional relationship between them. Specifically, while SL and cognitive flexibility exhibit the expected antagonistic interplay at lower levels of OC tendencies, this relationship progressively diminishes as OC tendencies increase. These findings

underscore the importance of moving beyond single-task paradigms and adopting cross-task approaches to capture how interactions between cognitive systems are organized across contexts. Future research employing multiple experimental paradigms will be essential to determine how such interaction-level alterations represent a core mechanism underlying OC or, in the long term, clinical OCD.

Our study identified the interaction between SL and the prefrontal cortex-related function, cognitive flexibility, with an across-task design. Nonetheless, the competitive memory systems hypothesis between executive functions and SL provides a theoretical framework that supports their interaction across four distinct levels.⁴⁸ At the most general level, correlational behavioral studies probe the relationship between executive functions and SL by employing independent tasks and testing for associations between their performance indices.^{6,54} In line with the present investigation, this approach targets enduring individual differences rather than transient states.⁴⁸ Even at this level, it captures core neurocognitive strategies: when prefrontal, control-dependent processes are less efficient, SL systems appear to compensate by shifting toward more implicit,

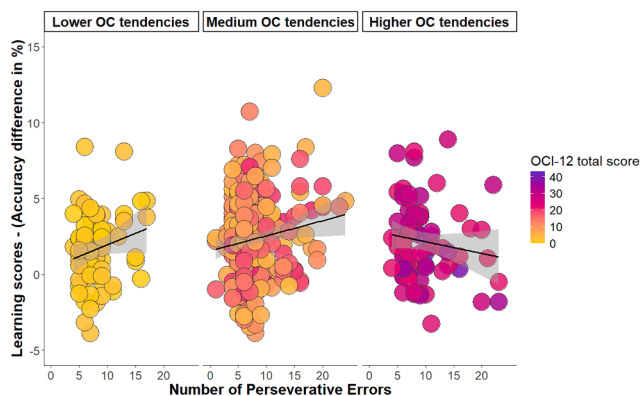


Figure 3. Relationship between cognitive flexibility and accuracy-based statistical learning across OCI-12 scores

The figure illustrates the relationship between cognitive flexibility, as measured by the number of perseverative errors on the card sorting task along the x axis, and statistical learning performance along the y axis, which is operationalized as the difference in accuracy between high- and low-probability triplets. Each point represents an individual participant, with color encoding their total OCI-12 score along a continuous gradient from low (yellow) through intermediate (pink) to high (purple) obsessive-compulsive tendencies. A linear regression line with 95% confidence intervals is overlaid in black. While the OCI-12 score was treated as a continuous variable in all statistical analyses, for visualization purposes, the data are faceted by the levels of OC tendencies. These levels represent varying degrees of OCI-12 scores, approximating one standard deviation below the mean (lower OC tendencies), at the mean (medium OC tendencies), and one standard deviation above the mean (higher OC tendencies), respectively. The color gradient used in the plot (yellow to pink to purple) visually reflects this increase in the level of OC tendencies. The figure highlights the moderating role of OC tendencies in the antagonistic association between statistical learning and cognitive flexibility. Specifically, the typical inverse relationship, where reduced cognitive flexibility is associated with enhanced statistical learning, was observed in participants with lower and medium OC tendencies. In contrast, this pattern was not present among individuals with higher OC tendencies, for whom statistical learning remained relatively stable across the cognitive flexibility continuum. This suggests a disruption of the typical trade-off between these cognitive functions in the context of OC tendencies.

automatized modes of processing. The second level adopts an interventional approach, in which executive functions are transiently disrupted or downregulated to test how reduced top-down control influences SL performance.^{36,55} This design supports stronger causal inferences about their interaction. At the third level, converging neurocognitive evidence indicates that similar reductions in frontal control can emerge spontaneously, without external intervention, and may likewise facilitate statistical learning when control-related networks become less engaged.⁵⁶ Finally, process-level approaches integrate executive functions and SL within a single task, enabling the simultaneous examination of their interaction under heightened cognitive demands.⁴⁸ By combining the core features of both systems, such paradigms capture real-time, state-dependent dynamics as they unfold during performance. Collectively, evidence across these four levels converges on the conclusion that executive functions and SL interact in systematic ways, with their relationship flexibly shifting between competition and cooperation depending on contextual demands.⁴⁸ Accordingly,

to better understand how OC tendencies relate to this interplay, future research should aim to investigate all four levels within a unified empirical framework.

Beyond demonstrating an individual-difference-dependent interaction between neurocognitive systems, our findings address an important gap by elucidating the interaction between unsupervised learning, a primary form of learning,³⁰ and executive functions among OC tendencies. Consistent with prior findings, unsupervised learning was found to be preserved,^{20,57–60} suggesting this core learning mechanism remains robust across OC tendencies similar to OCD, although not all prior findings are fully aligned with this pattern.^{61–65} This preservation is particularly noteworthy, as the excessive bias toward habitual behavior in OCD may partly stem from external reward-driven learning. In feedback- or reward-driven contexts, it is difficult to disentangle whether performance improvements reflect sensitivity to external reinforcement or strengthened stimulus-response associations. Moreover, individuals with OCD and OC tendencies may reach a ceiling effect more rapidly due to heightened reward or feedback sensitivity, thereby accelerating the shift toward enhanced automatic processes and reducing the opportunity for flexible behavioral adaptation. Although the pure learning mechanism remained intact, the interaction of SL with goal-directed functions became atypical among higher OC tendencies. This suggests that the disruption lies not within the pure learning mechanisms themselves, but in the dynamic interplay between these systems among OC tendencies and possibly, in OCD.^{10,12,52,66} Future research should further investigate the within-task interaction between habitual and goal-directed processes in relation to unsupervised learning mechanisms, particularly in the absence of external reward. This would clarify the fundamental relationship between habitual and goal-directed functions and their contribution to OC- and OCD-related behavioral manifestations.

Our findings underscore the importance of investigating not only individual neurocognitive functions but also their dynamic interplay in advancing our understanding of the roots of OC tendencies. Our results imply that the weakened interplay observed among higher OC tendencies could serve as a potential predictor of OC symptomatology.^{9,10,12,19,49} Alongside theoretical frameworks that propose a bias toward automatic processes in clinical OCD,^{10,12,19,26,29,49,66,67} other perspectives emphasize shifts in the relative engagement of neurocognitive systems, whereby performance may be supported by increased reliance on controlled, explicit processes to maintain effective performance.^{35,57,58,61,68,69} Prior behavioral and neuroimaging studies have shown that during unsupervised tasks, neural activity is predominantly associated with hippocampal and medial temporal lobe regions rather than striatal structures.^{59,60} Such patterns reflect differential contributions of these systems during task performance. While the typical antagonistic interaction between these systems is maintained among lower levels of OC tendencies, this pattern appears to weaken as tendencies increase within the non-clinical OC spectrum. This raises the possibility that, in clinical populations, such a shift could result in an increased reliance on explicit systems.⁵⁷ Our findings align with this perspective, as they suggest that the characteristics of both clinical OCD and OC tendencies may stem from the interactive

manner of neurocognitive systems.^{10,57,58,61,68,69} Furthermore, it can be speculated that whether these systems engage in competitive or cooperative interactions depends on the specific cognitive demands of the task, suggesting a context-sensitive dynamic rather than a static relationship. Therefore, future research is needed to determine whether this altered cognitive interplay persists in clinical OCD or whether clinical OCD involves different interaction dynamics between these cognitive processes.

Another noteworthy finding is that the unrevealed interplay with cognitive flexibility appeared only in the accuracy-based performance indicator of the ASRT task. This dissociation is particularly interesting as it raises the question of which performance components are more sensitive to OC tendencies. One possible explanation is that the CST relies on accuracy without imposing temporal constraints.⁴² Accuracy- and rule-based learning generally require more effortful processing,^{70–72} which may account for the antagonistic relationship between the two measures. Specifically, enhanced implicit adaptation to rule-based structures may come at the cost of reduced performance in tasks requiring explicit rule detection, an effect that aligns with the competition and cooperation framework outlined above.^{36,55} This pattern also reflects the clinical features of OCD, where symptoms often involve an excessive focus on order, regularity, and precision, such as checking, arranging, or striving for symmetry.^{7,73} Consequently, accuracy-based measures may be particularly sensitive to the influence of OC tendencies, rather than reaction time measures. In our analyses using the OCI-R, individuals with higher OC scores exhibited faster reaction times. However, this effect did not replicate when using the OCI-12, a shortened version aligned with the DSM-5.^{7,47,74,75} Given that the OCI-12 is derived from the same item pool, the disappearance of the effect following the removal of a subset of items suggests that the other finding with the OCI-R was not robust and is sensitive to the operationalization of the OC measure. Taken together, these findings suggest that OC symptoms may interfere more strongly with learning processes grounded in precision and rule detection, offering a clearer picture of how cognitive rigidity manifests in the disorder.

It is important to note that our study was conducted on an analogue sample, the so-called non-clinical adult population. Although OC tendencies in the general population share important phenomenological features with clinical OCD, and thus provide a relevant basis for theoretical inference, the current findings should not be generalized to clinical populations. Rather, they are best interpreted within a continuum-based framework. Spectrum approaches offer valuable theoretical and methodological tools for understanding clinical conditions, including OCD, by conceptualizing symptoms as continuously distributed and partially overlapping across individuals.^{9,14,20,24,76,77} Importantly, previous research has demonstrated that OC tendencies can influence a broad range of neurocognitive functions, including statistical learning,²⁰ inhibitory control,⁷⁸ cognitive flexibility,¹⁹ and decision-making.^{79,80} This can prove that this approach serves as an effective methodological tool for identifying individual differences in neurocognitive functions. The current study contributes to this growing body of literature by highlighting how OC tendencies may influence not just cognitive domains in isolation but the dynamic interplay between them, offering a more integrated

understanding of the neurocognitive profile associated with OC tendencies. Our findings indicate that while a dynamic interplay among neurocognitive functions is maintained at lower levels of OC tendencies, this interaction may potentially be absent in clinical populations, resulting in impaired adaptive behavior. This disruption could be anticipated by higher OC tendencies. It is also possible that this inverse relationship between these functions persists at the clinical level but manifests in an exaggerated, potentially nonlinear manner, consistent with a U-shaped function across the OC spectrum.

In this study, OC tendencies were assessed using a multidimensional scale comprising washing, checking, ordering, and obsessing, with analyses focusing on the variance shared across these domains. While this approach captures core OC-related variation, it does not allow firm conclusions regarding the specificity of the observed associations. In particular, it remains to be determined to what extent these patterns reflect processes specific to OC symptoms, as opposed to broader transdiagnostic factors such as anxiety or intrusive thought propensity. More broadly, these findings are consistent with contemporary dimensional frameworks of psychopathology, including the research domain criteria (RDoC)^{25,81–83} and the hierarchical taxonomy of psychopathology (HiTOP),^{84–86} which emphasize that psychiatric traits are continuously distributed and organized along interacting neurocognitive systems. Future work incorporating multiple symptom dimensions will be important for clarifying the specificity and generality of the observed effects.

To conclude, our results support the competitive memory systems hypothesis, which emphasizes an antagonistic relationship between neurocognitive systems,^{6,36,37,55} by elucidating a more general, individual-difference-dependent dynamic interplay between SL and goal-directed processes, here cognitive flexibility, and how their interaction is modulated by the prevalence of OC tendencies in a non-clinical population. While lower prevalence of OC tendencies may facilitate adaptive neurocognitive interactions, higher OC tendencies might represent early neurocognitive markers predictive of increased vulnerability to OCD. These results underscore the significance of conceptualizing OC tendencies as transdiagnostic traits to enhance early identification and inform tailored interventions. Importantly, our study highlights the necessity for cognitive neuroscience to transcend the examination of isolated neurocognitive functions and instead prioritize the investigation of their interactive dynamics, as the integrity of individual processes alone may mask critical dysfunctions emerging from their interactions.

Limitations of the study

Some limitations should be noted in the present study. First, the relatively high exclusion rate, a common challenge in online experimental designs,^{20,77,87,88} may have affected the generalizability of the findings. Although rigorous data quality checks were essential to obtain high-quality data, the inclusion criterion requiring the absence of any self-reported psychiatric or neurological history likely limited the representation of individuals with more pronounced OC tendencies. As a result, the upper range of the OC spectrum may have been underrepresented, potentially narrowing the scope of our conclusions. A key limitation of the present study is that we did not control for other conditions

that are frequently associated with elevated compulsivity and are often comorbid with OC tendencies, including anxiety and depressive symptomatology.^{9,89,90} Consequently, the present results do not allow us to fully isolate effects specifically related to the OC symptom dimension from those potentially driven by related affective or psychopathological factors. An additional limitation is that some participants exceeded commonly used clinical cutoffs on OC measures; however, in the absence of diagnostic assessment, it remains unclear whether these individuals meet the criteria for a formal OCD diagnosis. Presenting the tasks in a fixed order may have introduced potential order or fatigue effects. Future studies should therefore consider counterbalancing task order to minimize such influences, as performance on later tasks may be affected by declining attention or cognitive fatigue. Moreover, although cognitive flexibility was assessed using a CST, this measure has inherent methodological limitations.^{91,92} Therefore, future research would benefit from incorporating multiple measures of cognitive flexibility to obtain a more comprehensive assessment of executive functioning. Finally, the present study was conducted in a university-based adult sample, which may limit the generalizability of the findings to the broader population. Accordingly, future studies should extend these investigations to more diverse age groups and community samples to strengthen external validity.

Furthermore, OC tendencies were assessed using the OCI-based questionnaire, a widely used and psychometrically well-established measure. However, the OCI-R and its short forms consist of unidirectional items and do not include reverse-coded items. This feature has recently been identified as a potential source of bias in online studies. Sarna et al.⁹³ argue that questionnaires without reverse-coded items are more susceptible to acquiescence, that is, a general tendency to agree with items regardless of their content. In addition, they show that inattentive responding can inflate the endorsement of low base rate symptoms, which may lead to artificially elevated symptom scores and, in turn, to spurious associations with behavioral measures. Related concerns have also been raised by Zorowitz et al.,⁹⁴ who demonstrate that in online samples, careless or low effort responding can induce spurious correlations between task performance and psychiatric symptom measures, particularly when symptom distributions are positively skewed. Importantly, their findings suggest that standard quality control procedures based solely on behavioral task performance are often insufficient, as participants who respond inattentively on questionnaires are not reliably identified by behavioral exclusion criteria.⁹⁴ In the present study, we applied rigorous behavioral screening procedures to ensure high-quality task data. At the same time, we did not include questionnaire-level attention checks or infrequency items within the OCI measure. The only potential proxy for estimating such effects is the Autism Quotient,⁹⁵ as no additional questionnaires containing reverse-coded items were administered that would have allowed for the computation of an acquiescence index. Consequently, we cannot fully rule out the influence of acquiescence or inattentive responding on the observed associations. It is important to note that this limitation reflects a structural characteristic of the OCI instrument rather than a design choice specific to the present study. Addressing it more fully would likely require the development and validation of

revised OC symptom measures that incorporate reverse-coded items while maintaining strong psychometric properties. Future studies should therefore combine well-established clinical instruments with improved questionnaire design features, including reverse-coded items and embedded attention checks, in order to more directly assess and control for response biases in online data collection contexts.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by Prof. Dezső Németh, dezso.nemeth@inserm.fr.

Materials availability

This study did not generate new unique reagents.

Data and code availability

- Behavioral data have been deposited at OSF and are publicly available at <https://doi.org/10.17605/OSF.IO/FWB38>.
- All original code has been deposited at OSF and is publicly available at <https://doi.org/10.17605/OSF.IO/FWB38>.
- The behavioral tasks have been deposited at OSF and are publicly available at <https://doi.org/10.17605/OSF.IO/FWB38>.
- Any additional information required to reanalyze the data reported in this article is available from the [lead contact](#) upon request.

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AUTHOR CONTRIBUTIONS

B.B.: conceptualization, software, validation, investigation, data curation, formal analysis, writing—original draft, writing—review and editing, visualization; T.V.: conceptualization, software, validation, investigation, data curation, formal analysis, resources, writing—review and editing, supervision; funding; B.C.F. methodology, validation, writing—review and editing, F.H.: writing—review and editing; D.N.: conceptualization, software, validation, resources, writing—review and editing, supervision, funding.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT 4.0 to improve the writing style of our manuscript. The authors reject using AI for scientific purposes to gain unethical benefits. However, the authors believe that it helps the equality of native and non-native English speakers to have the same opportunities. Thus, the authors do recommend using generative AI for lingual purposes (only). After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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SUPPLEMENTAL INFORMATION

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Raw data	This paper, OSF	doi: https://doi.org/10.17605/OSF.IO/FWB38
Software and algorithms		
Experimental task code	This paper, OSF	doi: https://doi.org/10.17605/OSF.IO/FWB38
Analysis code	This paper, OSF	doi: https://doi.org/10.17605/OSF.IO/FWB38
Experimental tasks	This Paper, OSF	doi: https://doi.org/10.17605/OSF.IO/FWB38

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

A total of 568 university students took part in the study through an online experiment in exchange for course credit. The sample shows partial participant overlap with those reported in Brezóczi et al.,²⁰ Hann et al.,⁷⁷ and Nagy et al.⁹⁶; however, the datasets are not identical, as data were collected across multiple studies with different primary research aims and measurement protocols. To maintain data integrity, rigorous quality control procedures were implemented, resulting in the exclusion of 164 participants who failed to follow the instructions. Our goal was to meet multiple data quality criteria, which are outlined in detail in the ‘[quality control of the data](#)’ section below. The final sample consisted of 404 participants (285 female, 111 male, and 3 non-specified, 5 undisclosed $M_{Age} = 22.06$ years; $SD_{Age} = 5.09$). This study did not perform analyses based on sex or gender, which could limit the generalizability of the findings. Participants provided informed consent, and the studies received approval from the Research Ethics Committee of Eötvös Loránd University, Budapest, Hungary (2021/504), following the principles of the Declaration of Helsinki.

METHOD DETAILS

Alternating Serial Reaction Time task

Statistical learning was measured by the Alternating Serial Reaction Time (ASRT) task.^{40,41} The task was implemented in JavaScript using jsPsych version 6.1.0.^{97,98} Each trial presented a visual stimulus, an illustration of a dog’s head, in one of four horizontally aligned screen positions (Figure 1A). Participants were instructed to respond as quickly and accurately as possible by pressing the corresponding keyboard key (“S,” “F,” “J,” or “L” from left to right). The stimulus remained visible until a correct response was given, followed by a 120 ms response-to-stimulus interval before the next trial. Incorrect responses resulted in the stimulus remaining on the screen until corrected. Unbeknownst to participants, the stimuli followed a probabilistic eight-element sequence alternating between pattern and random elements (e.g., 2–r–4–r–3–r–1–r, where numbers denote fixed positions and “r” indicates a random one) (Figure 1B). This alternating structure resulted in some three-element combinations (triplets) occurring more frequently than others. High-probability triplets – such as 2–X–4, 4–X–3, 3–X–1, and 1–X–2, where X is the variable middle element – occurred more often due to their consistent alignment with the underlying sequence. High-probability triplets emerged either when two pattern elements enclosed a random element (50% of trials) or when two random elements enclosed a pattern element (12.5% of trials) (Figure 1C). Making up the remaining 37.5% of trials, low-probability triplets included less predictable element combinations based on the sequence structure.

The ASRT task consisted of 15 blocks, each containing 10 repetitions of an eight-element sequence, for a total of 80 stimuli per block. After each block, participants received feedback on their average accuracy and reaction time, whereas no information was provided about their statistical learning performance, as they were unaware that the task involved detecting a hidden regularity.

Card Sorting Task

Cognitive flexibility was assessed using the Card Sorting Task (CST), adapted from the Wisconsin Card Sorting Test (WCST), a well-established measure of executive function.^{42,98,99} The CST evaluates an individual’s ability to shift cognitive strategies in response to changing task demands. During the task, four reference cards are displayed simultaneously on the screen. Each card contains visual stimuli that differ along three dimensions: color (red, yellow, green, or blue), quantity (one to four items), and shape (triangle, star, diamond, or circle). In each trial, a separate target card appears beneath the reference cards (Figure 1D). Participants are instructed to match the target card with one of the four reference cards according to a common feature, either color, quantity, or shape, by

selecting the corresponding card. Importantly, the correct matching rule is not disclosed to the participant. Instead, participants are required to infer the rule based on feedback provided after each response, which indicates whether the selected card was correct or incorrect (Figure 1E). The task comprises a total of sixty-four trials. The underlying categorization rule changes after every sequence of ten consecutive responses. The order of rule changes follows a fixed sequence: first based on color, then shape, followed by quantity, and then repeats in the same order. Cognitive flexibility is measured by the number of perseverative errors, defined as repeated use of a previously correct but no longer valid rule. A lower number of perseverative errors indicates greater cognitive flexibility.

Obsessive-compulsive inventory

Obsessive-compulsive tendencies were assessed using the Obsessive-Compulsive Inventory–Revised (OCI-R,^{47,100}), a self-report questionnaire measuring the severity of symptoms on a 5-point Likert scale ranging from 0 (not at all) to 4 (extremely). Participants reported how much each symptom had bothered them during the previous month. For the present analyses, a 12-item version (OCI-12) was computed from the OCI-R by excluding the hoarding and neutralizing items, in line with the DSM-5 reclassification.⁴⁷ The OCI-12 has demonstrated strong psychometric validity, including high internal consistency and test-retest reliability.⁴⁷ Although it represents a relatively recent modification, its Hungarian version, derived from the validated Hungarian OCI-R, has not yet been independently validated. The Cronbach's alpha in our sample indicated good internal consistency ($\alpha = 0.89$). The total score can vary from 0 to 48. In our final sample, the observed scores ranged from 0 to 43 ($M = 12.58$; $SD = 9.02$); see Figure S1. For transparency, the full OCI-R analyses are reported in the supplemental information (Tables S7–S10).

Procedures

The experiment was conducted using the Gorilla Experiment Builder platform (<https://www.gorilla.sc>).¹⁰¹ It began with participants reading an informational briefing and providing informed consent. Subsequently, participants completed the ASRT task, which started with two practice blocks followed by 15 task blocks. The practice blocks consisted solely of random trials and were excluded from analysis. To assess participants' awareness of any patterns, we administered post-task inquiries asking them to report any regularities they may have noticed during the ASRT task. Specifically, participants were questioned about their detection of hidden sequences or patterns and asked to elaborate if applicable. None were able to accurately describe the alternating sequence, indicating that the task remained implicit, consistent with prior research.³³ Following the ASRT task, cognitive flexibility was evaluated using the CST, and obsessive-compulsive tendencies were measured with the OCI-12. Additionally, Autism Quotient was administered to assess for autistic traits,⁹⁵ demographic data on socioeconomic status, sleep, health, and handedness were collected. To account for potential confounding variables associated with the online setting, participants provided concise details about their testing environment, which are thoroughly outlined in the 'quality control of the data' section.

Quality control of the data

Online data collection is known to present several methodological challenges, as outcomes may be influenced not only by the psychological constructs of interest but also by variability in participants' response styles, engagement levels, and task completion strategies.⁹³ To address these concerns, we implemented data quality control procedures following established recommendations for online experimental research.⁸⁷ From the initial sample, we excluded participants who: 1) reported prior completion of the ASRT task ($N = 6$, 1.06%); 2) restarted or quit the experiment at any point ($N = 28$, 4.93%); 3) failed the attention test screening for non-compliance ($N = 26$, 4.58%); 4) whose mean raw accuracy on the ASRT task was below 80%, as such low performance was considered indicative of insufficient task engagement rather than genuine performance ($N = 24$, 4.23%); 5) were over 55 years old due to the potential influence of age-related cognitive decline on neurocognitive performance measures ($N = 1$, 0.17%); 6) reported neurological impairment or head injury, or reported a diagnosis of any psychiatric condition ($N = 58$, 10.21%); 7) reported having consumed alcohol within 6 hour, recreational drugs or psychoactive medications within 24 hour before the experiment ($N = 38$, 6.69%); 8) took long self-paced breaks between ASRT blocks, as such extended interruptions may indicate reduced task engagement ($N = 4$, 0.7%); 9) engaged in random button pressing during ASRT task ($N = 3$, 0.53%) and 10) participants who scored in the zero category on the CST, indicating random clicking during the task or incomplete understanding of it ($N = 19$, 3.34%). As some participants met multiple exclusion criteria, the combined criteria resulted in the exclusion of a total of 164 participants (28.87%).

QUANTIFICATION AND STATISTICAL ANALYSIS

Data preparation and analysis

Data preprocessing, statistical analysis, and visualization were carried out in R version 4.4.2.¹⁰² For the ASRT task, each trial was categorized according to whether it represented the final element of a high- or low-probability triplet. Only the first response for each trial was retained; subsequent responses were excluded to ensure response validity. Trials with reaction times (RTs) below 150 ms or above 1000 ms, as well as those falling beyond three absolute median deviations from each participant's median RT, were removed to control for outliers.²⁰ Repetition trials (e.g., 2–2–2, 1–1–1) and trills (e.g., 2–1–2, 3–2–3) were excluded due to their potential to elicit prepotent motor responses unrelated to statistical learning processes.^{33,103} The first two trials of each block were also removed, as they did not complete a triplet structure. Furthermore, incorrect responses were excluded from RT analyses.

Following these procedures, 17.54% of trials were excluded from accuracy analyses and 24.61% from RT analyses. These exclusion rates are consistent with those reported in online ASRT studies.^{20,77,96}

We utilized Linear Mixed Models (LMMs) for analyzing RT and accuracy performance. LMMs were fit with the mixed function from the *afex* package.¹⁰⁴ Regarding statistical learning and visuomotor performance, we computed the median reaction times and mean accuracy of the ASRT task for each participant in every block. These measures were used as outcome variables in linear mixed models with the Time (Block 1–15), Triplet Type (last element of a high-vs. low-probability triplet), Cognitive flexibility (Perseverative Error), OC tendencies (OCI-12 score), and their higher-order interactions as fixed effects in the model. The Time, OCI-12 score, and Perseverative Error factors were treated as mean-centered continuous variables. The models also included participant-specific intercepts and correlated slopes for the within-subject variables of Time and Triplet Type, treated as random effects. For RTs, the final model achieved convergence using the participants as random intercepts with by-participant correlated slopes for the Time. For accuracy, the final model achieved convergence using the participants as random intercepts with by-participant correlated slopes for Triplet Type and Time. Additional analyses conducted on further variables (Trials to Complete First Category, Total Number of Correct Responses) are reported in the [supplemental information \(Tables S5–S8\)](#).

Post hoc analyses involved the computation of estimated marginal means and marginal trends for simple effects and simple slopes, utilizing the *emmeans* package.¹⁰⁵ Significant interactions involving continuous predictors, specifically the OCI-12 score and Perseverative errors, were probed at three levels: the mean, as well as at ± 1 standard deviation from their means. For the Time factor, probing was performed at the end of the 5th, 10th, and 15th blocks. Figures were created with *ggplot2*.

In reporting the results, the main effects of Time are interpreted as an improvement in visuomotor performance, both on RT and accuracy, regardless of probabilistic patterns. Meanwhile, the main effect of Triplet Type is seen as an indicator of the amount of implicit probabilistic learning, and the interaction between Time and Triplet Type represents the temporal trajectory of statistical learning throughout the task. Please note that although we used the OCI-12 score as a continuous variable for all our analyses, for more illustrative data visualization and clarified post hoc analysis, we depicted results at lower OC tendencies (Mean OCI-12 score - SD), medium OC tendencies (Mean OCI-12 score), and higher OC tendencies (Mean OCI-12 score + SD), based on standard deviations from the mean. For the more complex interactions, the same approach was applied to the Number of Perseverative Errors.

Hence, our models were structured according to the following general form in *afex* syntax:

Reaction time:

Median RT ~ Time * Triplet Type * OCI-12 score * Perseverative Error + (Time | Participant).

Accuracy:

Mean Accuracy ~ Time * Triplet Type * OCI-12 score * Perseverative Error + (Time + Triplet Type | Participant).

6. General discussion

This dissertation aimed to characterize unsupervised learning mechanisms and their interaction with goal-directed control across non-clinical OC tendencies. Prominent theories emphasize an imbalance between habitual and goal-directed control processes (Gillan, Apergis-Schoute, et al., 2015; Gillan et al., 2011, 2014, 2016, 2020; Gillan & Robbins, 2014; Yu et al., 2024) as well as alterations in learning mechanisms, particularly implicit learning (Deckersbach et al., 2002; Goldman et al., 2008; Kathmann et al., 2005; Kelmendi et al., 2016; Marker et al., 2006; Vloet et al., 2010). However, a critical unresolved question concerns how a priori, unsupervised learning mechanisms, operating in a fully incidental manner, relate to OCD and non-clinical OC tendencies.

To address this gap, Study 1 systematically and critically reviewed the existing literature on unsupervised learning in OCD. This review revealed that prior studies failed to provide a clear and consistent account of pure unsupervised learning mechanisms. Specifically, methodological and conceptual limitations prevented the disentanglement of unsupervised learning from confounding factors such as task demands, goal-directed strategies, or explicit learning components. Building on these limitations, Study 2 focused on SL as a candidate pure unsupervised learning mechanism and examined its relationship with non-clinical OC tendencies. As adaptive learning involves not only the acquisition but also the updating of predictive representations, Study 2 further examined adaptation to changing environmental regularities. The findings showed that SL and the updating of predictive representations did not systematically vary with OC tendencies.

Within theoretical accounts that emphasize interactions between automatic learning and goal-directed processes in OCD, the presented findings raise an important interpretative question: at what cost is SL preserved? Study 3 offered insight into this issue by revealing a dynamic relationship between SL and cognitive flexibility, a core EF (Diamond, 2013; Friedman & Robbins, 2022; Miyake et al., 2000). In line with prior theoretical and empirical work (Ambrus et al., 2020; Nemeth et al., 2013; Pedraza et al., 2024; Virag et al., 2015), SL and cognitive flexibility were negatively associated, consistent with a competitive interplay between automatic learning mechanisms and goal-directed control functions. Notably, this inverse relationship became attenuated as non-clinical OC tendencies increased, suggesting that OC tendencies are associated not with isolated impairment in either process, but with alterations in their functional relationship. Together, these findings support an interactive memory-systems perspective in which OC-related neurocognitive variation is understood in terms of interactions among multiple systems rather than isolated dysfunctions.

The following sections integrate these findings and consider their theoretical, methodological, and clinical implications, as well as directions for future research.

6.1. Summary of Study 1

Study 1 reviewed eight studies examining unsupervised sequence learning in OCD, revealing mixed findings across distinct components of SRT performance: evidence for impaired sequence-specific learning, relatively preserved visuomotor learning, and generally slower RTs in individuals with OCD. However, drawing firm conclusions from this literature is challenging for several reasons. First, although all studies employed variants of the classical SRT task, they differed substantially in task design. These differences included the number and length of blocks, the placement (beginning of the task, within sequential blocks, etc.), and frequency of (practice) random blocks relative to sequence blocks, the number of stimuli, and the use of single versus

dual-task paradigms. Additional sources of variability included task instructions, response–stimulus interval durations, and, critically, the degree of explicit awareness of sequential regularities and individual differences within the OCD population. As a consequence of this methodological heterogeneity, findings across studies are difficult to compare directly. Moreover, not all task designs allowed for the systematic assessment of all relevant learning components. Accordingly, only a small subset of studies reported all three components (sequence-specific learning, visuomotor performance improvement, and general (baseline) RT) within the same experimental design (Deckersbach et al., 2002; Goldman et al., 2008). Beyond design limitations, this pattern may partly reflect a narrow focus on sequence-specific learning, defined as the acquisition of ordinal information, while other learning-related mechanisms have received comparatively less attention.

Beyond differences between studies, interpretation is constrained by the classical SRT task itself. The classical SRT task imposes a fundamental limitation on the clear dissociation of visuomotor performance improvement and sequence-specific learning (Janacsek et al., 2012). Such separation is only achievable under specific task configurations, for example, when extended random blocks are introduced either at the outset of the task or intermittently during task execution. In many studies, sequence-specific learning is inferred from RT differences between sequence blocks and random or altered-sequence blocks (Nissen & Bullemer, 1987). However, these differences do not necessarily reflect the acquisition of sequential structure per se, as they may partially arise from motor practice effects instead of the repeated exposure to the sequence. Consequently, behavioral performance on the classical SRT task alone provides limited leverage for determining whether observed differences reflect a genuine impairment in implicit sequence learning or are instead driven by task-related confounds and design constraints in OCD.

A further complication concerns explicit awareness. The simple and repetitive structure of deterministic SRT tasks can facilitate explicit knowledge of sequential regularities (Remillard, 2003, 2014). Indeed, follow-up assessments in some of the reviewed studies confirmed that participants had acquired explicit knowledge of the sequence (Goldman et al., 2008; Marker et al., 2006). Supporting this interpretation, explicitly informing individuals with OCD about the presence of a hidden sequence improved learning relative to standard instructions (Soref et al., 2018), suggesting that reducing uncertainty may facilitate strategic engagement with the task. Neuroimaging findings further complicate this picture: whereas classical SRT performance in neurotypical individuals primarily engages basal-ganglia systems (Janacsek et al., 2020), individuals with OCD showed greater recruitment of hippocampal, medial temporal, and orbitofrontal regions (Rauch et al., 1997, 2007). These patterns have been interpreted as reflecting greater reliance on explicit or declarative learning strategies, potentially compensating for altered implicit learning processes (Deckersbach et al., 2002; Soref et al., 2018, 2021; Ullman & Pullman, 2015). However, medial temporal and hippocampal involvement cannot be straightforwardly equated with explicit learning. More recent evidence indicates that these regions also contribute to the incidental extraction and consolidation of environmental regularities (Albouy et al., 2013; Schapiro et al., 2014, 2019). From this perspective, the activation patterns observed during SRT performance in OCD need not reflect a compensatory shift from implicit to explicit learning, but may instead indicate altered engagement or interaction among multiple learning and memory systems. This view is consistent with the interactive memory systems framework, which posits that multiple memory systems, including the basal ganglia and medial temporal lobe, operate in parallel, engaging in both competitive and cooperative interactions to

guide behavior depending on environmental demands (Ambrus et al., 2020; Nemeth et al., 2013; Pedraza et al., 2024; Poldrack et al., 2001; Virag et al., 2015). Determining whether these interactions are altered in OCD will require studies combining process-specific behavioral measures with neuroimaging.

Overall, Study 1 did not support a simple account of impaired implicit sequence learning in OCD. Rather, the available evidence suggests that observed differences may arise from multiple sources, including sequence-specific learning, general visuomotor performance, explicit strategies, and interactions among memory systems. These findings highlighted the need for paradigms that better isolate unsupervised learning while minimizing visuomotor and strategic confounds, providing the theoretical and methodological basis for the subsequent empirical studies.

6.2. Summary of Study 2

The aim of Study 2 was twofold and was addressed through two independent experiments (Experiment 1 and Experiment 2). Building on the gaps identified in Study 1, Experiment 1 examined the acquisition of probabilistic regularities using the ASRT task, whereas Experiment 2 extended this approach beyond acquisition to investigate the incidental updating of previously acquired predictive representations following changes in environmental regularities. Both experiments were conducted in university student samples across non-clinical OC tendencies. The results revealed robust SL across the spectrum of OC tendencies, as well as preserved updating of predictive representations, indicating that both the acquisition and flexible adaptation of probabilistic information remain largely intact in non-clinical OC populations.

6.2.1. Statistical learning – Experiment 1

Theoretical models addressing the development and maintenance of OCD predominantly focused on repetitive, maladaptive behaviors shaped by supervised, that is, reward- and feedback-driven learning mechanisms (Exner et al., 2014; Gillan et al., 2011, 2014; Hansmeier et al., 2018; Kelmendi et al., 2016; Zetsche et al., 2015). While informative, these approaches provided limited access to learning processes that operate independently of explicit reinforcement. The strong influence of feedback and outcome evaluation made it difficult to isolate core learning mechanisms from effects associated with feedback processing. Results from Study 2 showing preserved SL across non-clinical OC tendencies suggest that primary learning processes (Zhong et al., 2025) remain intact across levels of OC traits and are therefore unlikely, in isolation, to explain the emergence and persistence of OC tendencies and OC symptoms. Moreover, Experiment 2 of Study 2 showed that unsupervised learning can proceed efficiently, as reflected in the faster extraction of regularities in the absence of reinforcers. Although previous accounts have suggested that reward does not directly influence learning (Voon et al., 2015), it remained difficult to disentangle the pure acquisition of stimulus-response associations and statistical regularities from the influence of external reinforcement when they are actually present. In this respect, SL, where the acquisition of underlying regularities omits reinforcement, is clearly unaffected by external influences and highlights a preserved unsupervised primary learning process (Zhong et al., 2025). These results uncovered that supervision is not necessary for successful learning in individuals with OC tendencies. Expanding this conclusion will require the integration of additional unsupervised learning paradigms in future research.

Beyond its independence from supervision, SL provides a closer reflection of real-life learning compared with previous approaches. Traditional accounts have largely

assessed learning in OCD using deterministic patterns with rigid regularities and highly predictable associations - conditions that rarely occur in everyday situations (Barzilay et al., 2022; Deckersbach et al., 2002; Goldman et al., 2008; Marker et al., 2006; Rauch et al., 1997, 2007). Thus, in real-world contexts, relevant regularities are often embedded within noisy environments, where they are intermixed with largely irrelevant stimuli. It could be anticipated that the acquisition of such probabilistic and not fully predictable patterns would be attenuated in individuals with OC tendencies or OCD, given their characteristic pervasive doubt and intolerance of uncertainty (Dar, 2004; Fradkin, Adams, et al., 2020; Fradkin, Ludwig, et al., 2020; Marton et al., 2019). Contrary to this expectation, our findings demonstrated intact probabilistic learning performance, potentially as the inherent noise in the task limits uncertainty-driven strategic engagement (Soref et al., 2021). This interpretation is further corroborated by evidence from the WPT, in which the underlying probabilistic associations are generally acquired successfully (Exner et al., 2014; Hansmeier et al., 2018; Zetsche et al., 2015). Collectively, these results indicate that, in addition to preserved unsupervised learning mechanisms, the capacity to acquire information in noisy environments remains intact across non-clinical OC tendencies. To clarify the generality and boundaries of this effect, further research employing additional probabilistic paradigms will be necessary.

A further aspect highlighting the relevance of these results is that SL occurs in an implicit and incidental manner, as effectively demonstrated by the ASRT task, which preserves its complete implicitness (Horváth et al., 2022; Vékony et al., 2022). This finding is particularly relevant to Study 1, which highlighted the possibility that deterministic SRT paradigms promote explicit pattern search and strategic engagement in OCD. Interestingly, Soref et al. (2018) reported enhanced sequence learning when individuals with OCD were explicitly informed about the presence of a hidden regularity. Considered together, these findings raise the possibility that uncertainty-driven strategic search may be particularly disruptive when regularities are detectable but remain ambiguous, whereas learning may proceed efficiently when task structure is either made explicit or remains largely inaccessible to conscious strategy. This interpretation remains speculative and should be directly tested by systematically varying instructional conditions and awareness within the same probabilistic learning paradigm (Horváth et al., 2022; Howard & Howard, 1997; Vékony et al., 2022).

6.2.2. Updating of predictive representations – Experiment 2

Experiment 2 extended the investigation beyond initial acquisition by examining how previously learned probabilistic representations adapt to an unexpected change in environmental structure. Fine-grained analyses allowed the updating process to be decomposed into the persistence of previously acquired knowledge and the acquisition of new regularities (Horváth et al., 2022). Representations formed through SL are known to remain robust over both short and longer timescales, raising the question of whether such representations become excessively persistent across OC tendencies when environmental regularities change (Carden & Wood, 2018; Kóbor et al., 2017). The preserved updating observed in Experiment 2 is particularly relevant in light of previous findings showing altered adaptation to changing environmental information in OCD. Reduced sensitivity to outcome devaluation and contingency degradation suggests that previously acquired behavior can persist despite changes in outcome value or action–outcome contingencies (Gillan et al., 2011, 2014; Vaghi et al., 2019). Similarly, recent findings in volatile environments indicate altered confidence and error sensitivity during learning in OCD (Hoven et al., 2024), while computational accounts suggest repeated reliance on currently available environmental information to minimize uncertainty (Fradkin, Adams, et al.,

2020; Fradkin, Ludwig, et al., 2020). The present findings add to these accounts by showing that, when predictive representations are acquired incidentally through SL, previously acquired regularities can be maintained while newly emerging regularities are simultaneously acquired across OC tendencies. Thus, the updating of statistical representations itself appears to remain preserved despite the behavioral rigidity and altered use of prior information described in OCD.

Importantly, the present findings concern regularities that were both acquired and updated incidentally, without explicit instruction about the underlying structure or sequence-specific reinforcement. They therefore complement, rather than contradict, previous findings obtained in paradigms involving different forms of learning and behavioral adaptation. Together, these results suggest that difficulties in adapting previously learned behavior in OCD may not originate from the updating of statistical representations itself, but may emerge through additional processes involved in the use of acquired information to guide behavior. Further studies are needed to determine which cognitive processes and task conditions contribute to the altered behavioral adaptation observed in OCD.

Overall, Study 2 demonstrated that the core learning process, unsupervised SL, remains intact across individuals with non-clinical OC tendencies, along with the ability to update predictive representations in response to changes in environmental structure. These findings indicate robust primary learning and adaptive mechanisms across the OC spectrum. However, as suggested by the neurocompetition hypothesis, SL does not operate in isolation but interacts with multiple neurocognitive systems (Ambrus et al., 2020; Nemeth et al., 2013; Pedraza, Farkas, et al., 2024; Vékony et al., 2025). This perspective is consistent with theoretical accounts of OCD, including the habit hypothesis and compensatory memory systems framework, which emphasize that complex neurocognitive processes dynamically interact to support specific behavior. This raises the question motivating Study 3: does the balance between SL and goal-directed control change as OC tendencies increase?

6.3. Summary of Study 3

Study 3 aimed to reveal how non-clinical OC tendencies influence the well-established inverse relationship between unsupervised SL and EF, specifically, cognitive flexibility. We measured OC tendencies dimensionally in a university sample, trying to cover the full spectrum from low to higher non-clinical OC prevalence. SL was measured using the ASRT task, while cognitive flexibility was assessed via a Card Sorting Task. Consistent with prior theoretical and empirical work, SL and cognitive flexibility exhibited a negative association, reflecting a competitive interplay between automatic learning mechanisms and executive control function. Crucially, this relationship weakened with increasing OC tendencies: poorer cognitive flexibility was associated with enhanced SL at lower and medium levels of OC tendencies, whereas this association was no longer evident at higher levels. These findings suggest that unsupervised SL can remain intact across the OC spectrum, but its typical trade-off with cognitive flexibility changes as OC tendencies increase, pointing to an altered balance between automatic learning and goal-directed control functions. These findings extend theoretical accounts proposing an altered balance between automatic and goal-directed processes in OCD (Gillan, 2021; Gillan et al., 2011, 2014; Yu et al., 2024).

Previous work has predominantly examined this balance using outcome-devaluation and related instrumental paradigms, in which diminished goal-directed control is associated with greater habitual responding (Gillan et al., 2011, 2014; Vaghi et

al., 2019; Yu et al., 2024). Study 3 approached this question from a different perspective by examining SL as a fundamental unsupervised form of learning (Zhong et al., 2025) in relation to cognitive flexibility, a prefrontal cortex-dependent EF that underlies goal-directed behavior, and by assessing how this relationship is modulated by OC tendencies. Rather than indicating a straightforward shift toward stronger automatic processing, the present findings suggest that increasing OC tendencies are associated with a weakening of the typical relationship between these functions. At lower levels of OC tendencies, poorer cognitive flexibility was accompanied by enhanced SL, consistent with the competitive memory-systems framework (Ambrus et al., 2020; Nemeth et al., 2013; Pedraza et al., 2024; Vékony, Brezóczki, et al., 2025; Virag et al., 2015). As OC tendencies increased, however, this antagonistic relationship diminished, despite SL itself remaining intact. Thus, OC tendencies may be associated less with dysfunction within either function in isolation than with altered coordination between them (Banca et al., 2015; Gillan et al., 2011, 2016, 2020; Natsheh et al., 2019; Yu et al., 2024).

Building on this interpretation, we speculate that OC tendencies may modulate the functional significance of individual differences in executive functioning within the broader neurocognitive architecture, even in the absence of a direct association between OC tendencies and cognitive flexibility. At lower levels of OC tendencies, poorer cognitive flexibility was associated with better SL, consistent with a complementary relationship between these functions (Ambrus et al., 2020; Pedraza et al., 2024). As OC tendencies increased, however, this antagonistic relationship diminished, raising the possibility that comparable individual differences in EF may have different functional consequences across the spectrum of OC tendencies. Rather than reflecting a uniform executive deficit, higher OC tendencies may therefore be associated with changes in how EFs relate to other neurocognitive functions. Although this interpretation remains speculative, it generates a testable hypothesis that similar levels of executive performance may be associated with different neurocognitive profiles depending on OC tendencies.

One potential explanation for the divergence between our findings and earlier results lies in methodological differences across studies. Previous investigations have predominantly relied on outcome devaluation paradigms (Gillan et al., 2011, 2020; Yu et al., 2024), which assess habit and goal-directed control within a single experimental framework following extended instrumental training at the process level. In these paradigms, goal-directed control is inferred from the ability to flexibly adjust behavior in response to changes in contingencies and feedback, a process that additionally recruits multiple neurocognitive mechanisms related to reward-driven learning (Gillan et al., 2011, 2020; Yu et al., 2024). In contrast, the present study employed separate tasks to assess SL and cognitive flexibility, thereby targeting relatively stable, trait-like individual differences in their cross-task relationship (Horváth et al., 2025). Moreover, only one component of executive functioning was measured, raising the possibility that distinct executive processes may interact differently with SL as a function of OC tendencies. Importantly, the present study also examined this balance through component processes rather than habitual and goal-directed behavior directly. Whereas habit-based paradigms contrast habitual and goal-directed behavioral control, the present study focused on SL as a mechanism contributing to the acquisition of automatic behavior (Horváth et al., 2022; Kaufman et al., 2010) and cognitive flexibility as an executive component supporting goal-directed control (Friedman & Robbins, 2022). Thus, the present findings do not necessarily contradict the habit hypothesis, but may provide insight into processes underlying the broader imbalance it proposes and suggest that this balance may depend on the level at which the interaction is examined.

The present pattern raises the possibility that within-task and cross-task interactions capture partly distinct aspects of the balance between automatic and goal-directed processes. At lower and medium levels of OC tendencies, lower cognitive flexibility was associated with enhanced SL, whereas this association was no longer evident at higher levels of OC tendencies. Rather than indicating a simple shift toward stronger or weaker automatic learning, increasing OC tendencies therefore appear to weaken the typical relationship between SL and cognitive flexibility. One possibility is that higher OC tendencies constrain the competitive or compensatory interactions through which these functions normally influence one another, although the underlying neural mechanisms were not directly measured. Future studies integrating SL and executive control within the same paradigm will be necessary to determine whether this altered cross-task relationship also emerges when both processes compete directly during behavior, and ultimately how these process-level interactions relate to the broader balance between habitual and goal-directed control in OCD (Gillan, 2021; Gillan, Apergis-Schoute, et al., 2015; Gillan et al., 2014; Robbins et al., 2019).

6.4. Overall implications

Taken together, the findings of the three studies demonstrate that both unsupervised learning mechanisms and non-clinical OC tendencies are critical for understanding OCD, each offering unique insights, but yielding the most comprehensive account when considered in an integrated manner. Addressing limitations of previous approaches (Study 1), we found that unsupervised SL remains intact in individuals with non-clinical OC tendencies, as does the updating of predictive representations (Study 2). However, these preserved learning processes appear to come at the cost of a shift in the balance between SL and cognitive flexibility (Study 3). In the following section, I discuss the theoretical, methodological, and applied implications of the presented studies.

6.4.1. Theoretical implications of the presented studies

A key theoretical implication of the studies presented in this dissertation is that it directs attention to a fundamental mechanism of learning, unsupervised learning, specifically SL in OCD research (Zhong et al., 2025). Historically, models of OCD have largely emphasized supervised, reward-driven learning (Exner et al., 2014; Gillan, 2021; Gillan, Apergis-Schoute, et al., 2015; Gillan et al., 2011, 2014; Gillan, Otto, et al., 2015; Hansmeier et al., 2018). Besides providing valuable insights, these models make it difficult to isolate pure learning processes from reward contingencies and other confounding factors. Such processes have been described as secondary learning systems, building upon the neuroanatomical foundations provided by unsupervised learning (Zhong et al., 2025). Examining this primary mechanism was especially important in OCD and in individuals with OC tendencies, given that the disorder also involves disruptions in reward processing (Alves-Pinto et al., 2019; Figeo et al., 2011; Kaufmann et al., 2013), which may have influenced previous interpretations of learning performance in this population. By shifting the focus to unsupervised learning, our findings extend existing models by demonstrating that this primary mechanism remains intact across the spectrum of OC tendencies. The preservation of unsupervised learning suggests that the foundational capacity to extract regularities from the environment by mere exposure is preserved, potentially supporting the acquisition of subsequent skills, habits, and routines (Arciuli, 2018; Bogaerts et al., 2022; Conway, 2020; Horváth et al., 2022). Importantly, these findings demonstrate that unsupervised learning remains intact across the spectrum of OC tendencies. At the same time, the results clearly indicate that this unsupervised

mechanism (SL) alone can not account for the maladaptive symptom manifestations observed in compulsivity or OCD, highlighting the need for further research to identify the processes underlying the disorder's characteristics. Future research should also extend the present findings with clinically diagnosed OCD populations to determine whether the observed subclinical patterns generalize to clinical symptomatology.

Taken together, these findings allow us to speculate more broadly about learning-related difficulties across the spectrum of OC tendencies and even in OCD. Previous studies of supervised learning have shown that successful learning does not necessarily lead to flexible behavioral adaptation in OCD, as acquired action–outcome knowledge may remain intact despite persistent responding following changes in outcome value (Gillan et al., 2011, 2014; Gruner et al., 2016). Our findings raise the possibility that a similar dissociation may also apply to a more fundamental, feedback-free form of learning. Across our studies, statistical regularities were successfully acquired, and their representations could also be updated when the environmental structure changed. We therefore speculate that difficulties associated with OC may not primarily arise from an impaired capacity to extract or update environmental regularities, but rather when this acquired and updated information needs to be integrated with goal-directed functions to support flexible behavioral adaptation (Gruner et al., 2016). This possibility further highlights the importance of considering preserved learning functions in relation to other neurocognitive functions involved in behavioral adaptation.

Extending this framework further highlights the importance of examining cognitive processes not in isolation but in terms of their dynamic interactions. Traditional approaches in cognitive neuroscience have often assessed single processes within specific populations, leading to models that characterize OCD in terms of isolated deficits, such as impaired executive functioning, particularly cognitive flexibility (Chamberlain et al., 2007, 2008; Menzies et al., 2007; Tomiyama et al., 2019), or disrupted implicit information processing (Goldman et al., 2008; Kathmann et al., 2005; Marker et al., 2006). A broader perspective suggests that these processes interact systematically (Ambrus et al., 2020; Nemeth et al., 2013; Pedraza et al., 2024, 2025; Vékony, Brezócski, et al., 2025). Consistent with frameworks such as the habit hypothesis and the compensatory memory system, which emphasize the interplay of multiple cognitive processes in OCD, we show that interactions between neurocognitive mechanisms can provide a more accurate prediction of an individual's position along a psychiatric continuum than any single process alone (Gillan et al., 2016, 2020). Alternatively, this interaction may persist in an exaggerated or nonlinear form, consistent with a U-shaped function across the OC spectrum. These findings underscore that future research on OC tendencies should not only evaluate single cognitive functions but also systematically consider how the performance of a given function may be shaped by its interactions with other processes.

Critically, the relationship may also be reciprocal: if neurocognitive processes can predict psychiatric symptoms, then specific symptoms or traits may themselves provide insight into the underlying neurocognitive mechanisms (Gillan et al., 2016, 2020; Scholl et al., 2022). Recent evidence even suggests that such dimensional phenotypes can be more effective than clinical diagnoses alone in identifying neurocognitive alterations related to symptoms or traits (Gillan et al., 2016, 2020; Scholl et al., 2022). In line with this perspective, our studies were conducted in a non-clinical sample of healthy young adults exhibiting a range of OC tendencies. This dimensional approach offers a sensitive theoretical framework for capturing meaningful individual differences within heterogeneous disorders such as OCD (Abramowitz et al., 2014; Colzato et al., 2025; De Bruijn et al., 2010; Fineberg et al., 2013; Gillan & Rutledge, 2021; Hoven et al., 2024).

Traditional, binary models of psychopathology have often assumed that brain structure or function is intact below a clinical threshold and altered above it, corresponding to the presence or absence of a diagnosis. However, there must be a continuous transition between these extremes, which can help explain the considerable individual variability in behavior and symptom expression (Abramowitz et al., 2014; Buchweitz et al., 2026; Gillan et al., 2016, 2020). Our findings emphasize this point and extend the spectrum-based approach by suggesting that neurocognitive processes should be examined not only when an individual's behavior deviates from the norm, but also across varying traits and phenomenological dimensions. Many traits, such as compulsivity, are transdiagnostic, appearing across conditions like OCD, addiction, eating disorders, and others, and can provide complementary information to enhance our understanding of human brain function (Colzato et al., 2025; Gillan et al., 2016, 2020; Robbins et al., 2024; Ruan et al., 2024). Taken together, these considerations strongly support the need for further spectrum-based research to map the relationships between traits, symptoms, and neurocognitive processes.

6.4.2. Methodological implications of the presented studies

A central methodological contribution of this dissertation is the consistent use of probability-based, implicit paradigms that enable a more precise assessment of unsupervised learning while addressing key limitations in prior OCD research. Previous studies on learning in OCD have been constrained by several methodological issues, which the present work tackles from multiple angles. First, such paradigms capture unsupervised learning by allowing participants to acquire hidden patterns through practice without external reinforcement. In the present studies, the ASRT task served as one suitable example of this approach. As shown in Study 1, it helps overcome limitations of the classical SRT task by dissociating visuomotor performance from SL while preserving implicit processing (Horváth et al., 2022; Janacsek et al., 2012; Vékony et al., 2022). This separation allows for a more precise assessment of learning mechanisms, with reduced confounding from motor execution. Moreover, because these tasks rely on the incidental acquisition of probabilistic regularities rather than fixed sequences (Howard & Howard, 1997; Janacsek et al., 2012), and do so without explicit instructions or reinforcement, they capture an important feature of real-world learning, in which regularities are often probabilistic rather than fully deterministic. This makes such paradigms particularly well-suited for investigating individual differences in learning in OCD, as they directly address several weaknesses identified in earlier research (Howard & Howard, 1997; Janacsek et al., 2012; Soref et al., 2018, 2021). Importantly, the ASRT represents only one possible implementation of this broader methodological approach. Future research on OCD would benefit from incorporating a wider range of unsupervised, implicit, probability-based paradigms with similar characteristics to complement and extend the present findings.

A second methodological implication concerns the level at which interactions between learning and EF are examined. The present cross-task approach complements earlier within-task paradigms by assessing individual differences in the relationship between SL and cognitive flexibility across separate tasks (Barzilay et al., 2022; Deckersbach et al., 2002; Gillan et al., 2011, 2014; Yu et al., 2024). Such associations may capture relatively stable differences in the functional relationship between cognitive processes, whereas integrated paradigms allow their interaction to be examined directly within a specific behavioral context. Horváth et al. (2025) further highlight additional layers of analysis. One involves experimental manipulation, where EFs are transiently disrupted or downregulated to assess how reduced top-down control affects SL (Ambrus

et al., 2020; Nemeth et al., 2013; Virag et al., 2015). Applying this approach to OCD could be particularly informative, given evidence that executive-control capacity influences treatment outcomes. By temporarily modulating top-down processes, this design enables stronger causal inferences about the interplay between automatic and goal-directed systems in symptom expression. A third level of analysis considers spontaneous fluctuations in EF networks (Simor et al., 2025; Vékony, Brezóczki, et al., 2025; Vékony, Farkas, et al., 2025). Even without direct intervention, periods of reduced top-down engagement appear to facilitate SL, suggesting that temporary disengagement of control-related systems may promote adaptive learning mechanisms. In the context of OCD, exploring these dynamics over the long term, potentially through mindfulness or mind-wandering phenomena, could reveal how naturally occurring shifts in cognitive control contribute to symptom regulation or resilience (Ahmari et al., 2013; Bourne et al., 2012; Jaafari et al., 2012). Finally, integrated paradigms can assess SL and executive control within the same task, capturing their moment-to-moment interaction under direct competition. Taken together, these complementary levels provide a methodological framework for determining when and how automatic learning and executive control interact in relation to OC tendencies.

A further methodological strength of the empirical studies is the use of online experimental designs. Online methods have the potential to fundamentally transform psychiatric and neuroscience research in the long term, as they enable the recruitment of large and demographically diverse samples, increase statistical power, and support standardized, precise, and reliable task presentation and data collection, thereby facilitating reproducibility (Donegan & Gillan, 2022; Gillan & Rutledge, 2021). In addition, online platforms are time-efficient, reduce experimenter-related biases, and allow participants to complete tasks in their natural environments. This may enhance the ecological validity of measured cognitive processes, such as learning and decision-making (Donegan & Gillan, 2022; Gillan & Rutledge, 2021). At the same time, online data collection introduces challenges, including environmental distractions and variability in participants' devices. Furthermore, some responses may be noisy and may not accurately reflect the targeted psychological constructs, but rather factors such as inattention or fatigue (Donegan & Gillan, 2022; Gillan et al., 2025; Rodd, 2024; Sarna et al., 2026). Appropriate screening procedures, task-specific quality controls, and replication across online and laboratory settings are therefore essential. Nevertheless, accumulating evidence suggests that well-controlled online cognitive experiments can produce reliable findings comparable to laboratory-based research (Gillan et al., 2025; Rodd, 2024). Combined with dimensional assessment, large-scale online experimentation therefore provides a useful methodological approach for detecting subtle individual differences in neurocognitive processes that may remain obscured by group-level comparisons.

6.4.3. Applied implications of the presented studies

The theoretical and methodological approaches outlined above also have important practical implications. In particular, the present findings suggest that the characterization of OC tendencies may benefit from considering neurocognitive processes in combination rather than relying solely on individual functions or symptom severity. Although SL and the updating of predictive representations remained largely robust across non-clinical OC tendencies, the relationship between SL and cognitive flexibility varied across levels of OC tendencies. Thus, potentially relevant neurocognitive information may lie not only in the efficiency of individual processes, but also in their functional relationships. If

replicated in clinical and longitudinal studies, such interaction-based measures could complement symptom-based assessment and contribute to a more fine-grained characterization of individual cognitive profiles. Extending this dimensional perspective longitudinally could help determine whether individual differences in such neurocognitive profiles precede changes in OC symptoms and may therefore serve as early indicators of vulnerability to clinically significant OCD (Abramowitz et al., 2014; Colzato et al., 2025). In the longer term, identifying reliable neurocognitive indicators of vulnerability could support earlier monitoring and preventive intervention, although their predictive validity and clinical utility remain to be established.

Beyond OCD-specific traits, the potential relevance of these neurocognitive profiles may extend across psychiatric conditions. Many psychiatric traits and symptoms are transdiagnostic, and shared underlying neurocognitive mechanisms may contribute to their expression across traditional diagnostic boundaries (Colzato et al., 2025; Cuthbert & Insel, 2013; Gillan et al., 2016). Consistent with the dimensional and transdiagnostic perspectives of HiTOP and RDoC, this raises an important applied question regarding whether the neurocognitive patterns associated with OC tendencies are specific to OCD or reflect broader mechanisms shared across psychopathology (Cuthbert & Insel, 2013; T. Insel et al., 2010; T. R. Insel, 2014; Kotov et al., 2017, 2021; Mittal & Wakschlag, 2016). Future research including multiple symptom dimensions and psychiatric conditions could help disentangle shared and disorder-specific neurocognitive mechanisms. Ultimately, identifying which neurocognitive profiles map onto specific symptoms or broader transdiagnostic traits may improve the characterization of individual differences beyond diagnostic categories and provide a more precise basis for clinical assessment and intervention.

This perspective may be particularly relevant to psychological treatment, as cognitive-behavioral therapy with exposure and response prevention (CBT/ERP) fundamentally relies on learning and the adaptive modification of behavior through experience. During ERP, patients repeatedly encounter obsession-related cues while refraining from compulsive responses, providing opportunities to revise previously established expectations about threat and the perceived necessity of compulsive behavior (Abramowitz, 2006; Öst et al., 2015). Contemporary inhibitory-learning accounts further emphasize the acquisition of new associations that compete with existing threat representations rather than the simple elimination of fear responses (Craske et al., 2014). From this perspective, individual differences in learning and the updating of previously acquired representations may influence how efficiently patients acquire, integrate, and generalize corrective information during treatment. The present findings further suggest that it may be informative to consider these learning processes in relation to executive control, rather than independently, given that the relationship between SL and cognitive flexibility varied across OC tendencies. Assessing these neurocognitive processes before and during treatment may therefore provide a more fine-grained characterization of individual cognitive profiles and could be examined prospectively as potential predictors of variability in therapeutic response (Kathmann et al., 2022). Such information could ultimately inform treatment stratification and personalization, for example by identifying individuals who may benefit from more intensive or differently structured learning opportunities or from therapeutic components targeting specific difficulties in learning, updating, or behavioral adaptation (Pereira de Souza et al., 2026). More broadly, integrating symptom profiles with neurocognitive mechanisms is consistent with RDoC-informed and precision-psychiatry approaches, shifting the focus from diagnosis and symptom severity alone toward the functional processes that may shape individual

treatment needs and outcomes (Baek et al., 2026; Hirschtritt et al., 2017; Kathmann et al., 2022; Starcevic & Brakoulias, 2008).

An additional implication concerns the scope of conventional cognitive assessment. Standardized clinical and neuropsychological batteries predominantly assess cognitive functioning under explicit task instructions and deliberate, goal-directed conditions. Widely used instruments, such as the Wechsler Adult Intelligence Scale (Valentine et al., 2020; Wechsler IV, 2010), as well as neuropsychological measures, provide important information about general cognitive ability and EFs, including cognitive flexibility, inhibitory control, processing speed, and working memory. However, conventional assessment places considerably less emphasis on implicit and incidental aspects of cognition, including the acquisition of environmental regularities, implicit learning, and the updating of previously acquired representations. Incorporating measures of these processes may therefore provide complementary information about neurocognitive functioning that is not readily captured by explicitly instructed tasks. Importantly, their clinical value may lie not only in their assessment in isolation, but also in examining how implicit learning processes interact with established measures of executive and general cognitive functioning. Such an integrative approach may reveal individual neurocognitive profiles arising from different configurations of implicit and explicit cognitive processes that would remain undetected when either is considered alone. From an RDoC-informed perspective, broadening cognitive assessment to encompass both explicitly controlled and more implicit forms of cognition, and their interactions, may provide a more comprehensive functional characterization of individual differences relevant to psychopathology and treatment response.

The applied value of these findings therefore lies in extending conventional symptom-based and cognitive assessment to include implicit learning mechanisms and their interaction with executive control. Such an approach aligns with a precision psychiatry perspective and may ultimately support more individualized assessment and intervention. In the longer term, if validated as reliable indicators of vulnerability, neurocognitive measures could also contribute to early identification and accessible digital screening in community, educational, or workplace settings, thereby extending their potential relevance from individualized care to broader preventive and public mental health initiatives.

6.5. Limitations of the presented studies

Although the present dissertation adopted a dimensional approach by examining OC tendencies continuously, its empirical scope remained largely specific to OC symptomatology. We did not systematically assess common comorbid dimensions, such as anxiety and depression, or extend the analyses to other forms of psychopathology in which similar neurocognitive alterations may occur (Basso et al., 2001; Choi et al., 2020; Goodwin, 2015; Kim et al., 2019; Lee et al., 2020). Consequently, the present findings cannot establish whether the observed associations with learning and executive functioning are specific to OC tendencies or reflect broader transdiagnostic processes. In particular, an important unresolved question is whether these associations characterize OC symptomatology itself or instead reflect an underlying dimension of compulsivity that is strongly expressed in OCD but extends across multiple psychiatric conditions (Donegan et al., 2025; Gillan et al., 2020; Robbins et al., 2024; Ziegler et al., 2019). Addressing this distinction will require future studies to simultaneously assess OC symptoms, compulsivity, and a broader range of psychopathological dimensions within the same individuals. Such an approach would allow the relative specificity and overlap

of their neurocognitive correlates to be directly tested, moving beyond a disorder-centered dimensional account toward the cross-diagnostic characterization of neurobehavioral mechanisms emphasized by RDoC and the empirically derived dimensional organization of psychopathology proposed by HiTOP. Notably, existing evidence already suggests that OC tendencies explain unique variance in neurocognitive functioning beyond correlated anxiety and depressive symptoms in non-clinical populations (Fradkin, Ludwig, et al., 2020; Loosen & Hauser, 2020), providing an important starting point for this broader investigation.

Second, the theoretical interpretations advanced here remain tentative, as they have not yet been tested in clinical OCD populations, in which OC-related mechanisms may manifest differently. Replicating these findings in individuals with diagnosed OCD is therefore critical for determining whether the neurocognitive associations observed along the non-clinical spectrum generalize to clinically significant symptom levels. Importantly, however, clinical OCD should not be treated as a homogeneous endpoint of this continuum (Mataix-Cols et al., 2005). The disorder comprises partially distinct symptom dimensions, including contamination/washing, checking, symmetry/ordering, and unacceptable thoughts, which may differ in their underlying neurocognitive profiles (Bragdon et al., 2018; Leckman et al., 2007; Mataix-Cols et al., 2005; van den Heuvel et al., 2008). Future studies should therefore examine whether alterations in SL and executive functioning are shared across OCD or preferentially associated with specific symptom dimensions or clinical subgroups. Such work would help determine whether the mechanisms identified here represent general features of OCD or contribute to its marked phenotypic heterogeneity.

Additional limitations pertain to sample characteristics: the exclusive use of university students, with a restricted range of OC prevalence, limits both population representativeness and variability along the OC spectrum. Moreover, the cross-sectional nature of the empirical studies prevents conclusions about the temporal relationship between neurocognitive processes and OC tendencies. It therefore remains unknown whether alterations in the relationship between SL and cognitive flexibility precede changes in OC symptoms, emerge alongside them, or develop as their consequence. Longitudinal and developmental studies across more diverse populations will be necessary to characterize how these relationships evolve over time and whether they have predictive value for symptom trajectories.

Furthermore, the present dissertation operationalized both SL and EF using a limited set of experimental measures. While SL remained intact across OC tendencies in the ASRT task used in the present dissertation, learning performance may vary across paradigms and stimulus modalities, and previous studies using classical SRT tasks have yielded mixed findings in OCD. Future research should therefore examine whether the present results generalize across complementary SL paradigms, including temporal, visual, and auditory regularities. Similarly, cognitive flexibility was examined as an EF supporting goal-directed behavioral control, but other complementary EFs, such as inhibition, working-memory updating, and planning, were not systematically assessed (Diamond, 2013; Friedman & Robbins, 2022). Importantly, the present measures capture specific components of these broader functional systems: SL reflects a fundamental mechanism supporting automatized behavior (Horváth et al., 2022; Kaufman et al., 2010), whereas cognitive flexibility represents one executive component contributing to goal-directed control (Friedman & Robbins, 2022). This distinction is theoretically important because goal-directed behavior depends on the coordinated contribution of multiple executive processes, which are partially dissociable and may rely on distinct neural circuits (Vaghi et al., 2017). Consequently, an apparent alteration in goal-directed

functioning may arise from disruption of different underlying cognitive mechanisms across individuals. Future studies should therefore combine multiple measures of SL with a broader battery of EFs and, where possible, more direct measures of goal-directed and habitual control. Such a multimethod approach would help determine whether the present findings reflect task-specific effects or more general neurocognitive alterations, while allowing the specific mechanisms contributing to impaired adaptive control in OC tendencies to be more precisely identified.

Another important limitation concerns the scope of learning-related processes investigated. While Study 1 highlighted the importance of disentangling learning components and the ASRT task enabled such separation, the present studies primarily focused on SL. Although improvements in visuomotor performance were observed across RT and accuracy indices, these effects did not show consistent associations with OC tendencies, limiting the strength of theoretical inferences. Baseline performance measures also yielded inconsistent results: RT was stable, whereas accuracy varied across experiments, showing higher, lower, or no differences. Thus, although the present findings provide a relatively consistent picture of SL, they do not allow similarly clear conclusions regarding more general aspects of task performance. The factors driving these inconsistencies could not be resolved within the present dissertation, underscoring the need for further research. Finally, in the absence of neuroimaging data, inferences regarding the underlying neural mechanisms remain necessarily indirect, based solely on behavioral performance. Given that neurobiological alterations in OCD may not be fully reflected in behavior (Deckersbach et al., 2002; Hansmeier et al., 2018; Rauch et al., 1997, 2007), future studies should integrate behavioral and neurobiological measures to achieve a more comprehensive understanding of OC-related cognitive processes.

7. Conclusion

This dissertation aimed to elucidate the role of SL in OC phenomena, with a particular focus on non-clinical OC tendencies and its relationship with goal-directed control. Prevailing theoretical models have emphasized imbalances between habitual and goal-directed control, as well as alterations in learning processes. However, the role of a priori, fully incidental unsupervised learning mechanisms has remained uncovered. The present findings demonstrate that SL, as a fundamental, unsupervised process, remains intact across varying levels of OC tendencies, together with the ability to update predictive representations in response to changing environmental regularities. Thus, the absence of associations between OC tendencies and either the acquisition or updating of statistical information argues against a primary role of these learning processes alone in explaining its behavioral manifestations. Critically, variability along the OC spectrum is not explained by impairments in learning per se, but by systematic changes in the association between SL and cognitive flexibility. These results support interactive memory systems frameworks by showing that the interplay between neurocognitive functions, rather than isolated dysfunctions, better characterizes the behavioral profiles of OC tendencies. Accordingly, the present findings extend existing learning-based models of OCD by suggesting that OC-related differences may lie not in a fundamental learning mechanism itself, but in how this mechanism operates in relation to executive control. Methodologically, they also advance the field by examining learning within a novel framework that treats OCD not as a homogeneous clinical disorder but as a continuum, capturing individual differences. Taken together, these findings suggest that the role of SL in OC phenomena may lie not in an impairment of this fundamental learning mechanism itself, but in its altered relationship with executive control. In the long term,

these insights may inform the refinement of clinical approaches to OCD and contribute to the development of integrative interventions that target interacting cognitive processes rather than isolated functions.

8. References

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9. Supplementary Materials

9.1. Supplementary Materials of Study 2

Supplementary Materials

Individual differences in probabilistic learning and updating predictive representations in individuals with obsessive- compulsive tendencies

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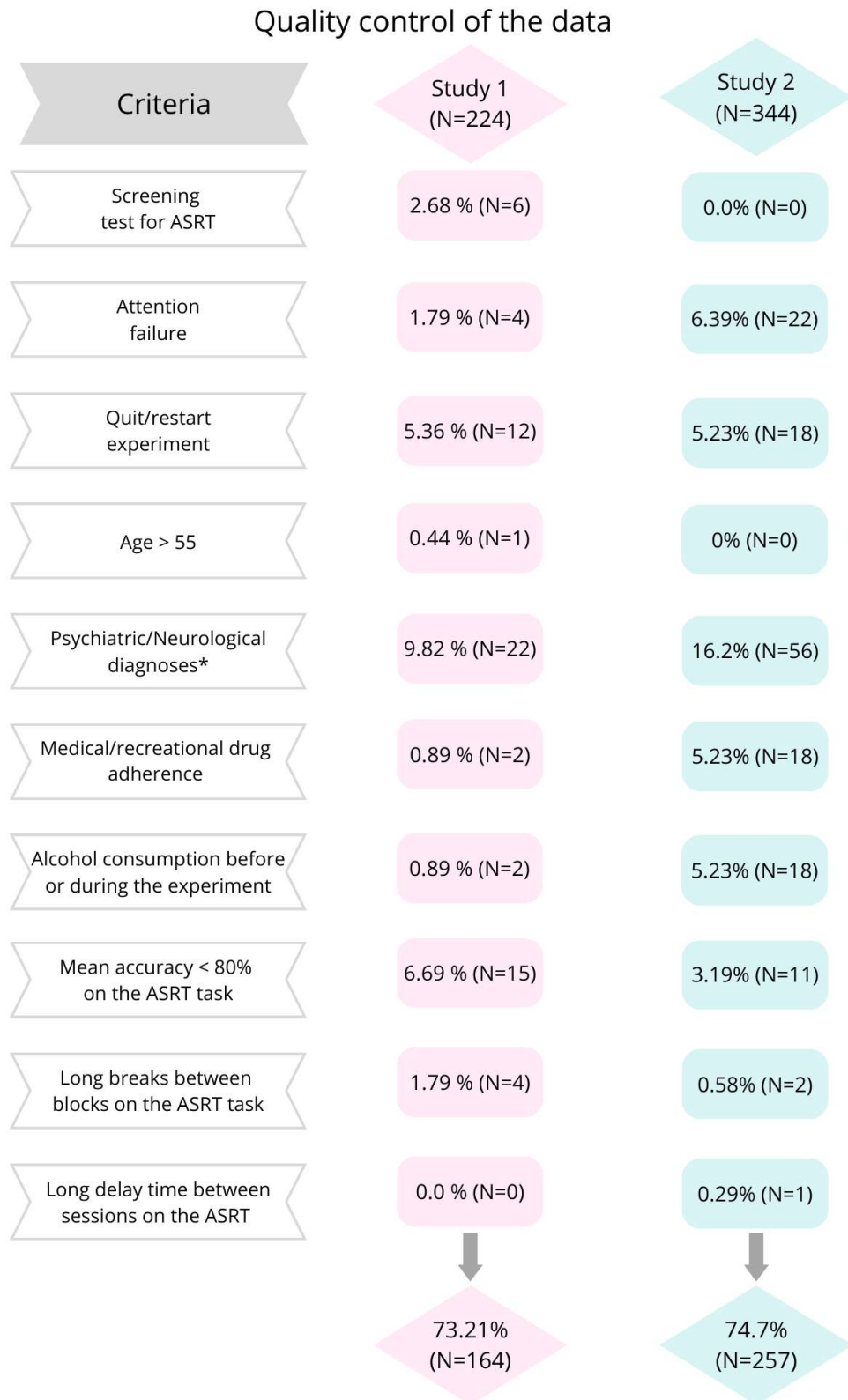
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Supplementary Figure S1. Flow chart of quality control of the data. Since some participants met multiple exclusion criteria, a total of 60 participants were excluded from Study 1, resulting in a final sample comprising 73.21% of the initial participants. In Study 2, 87 participants were excluded, leaving 74.7% of the participants in the final sample.

*Based on self-reported neurological impairment, Epilepsy or head injury, or reported diagnosis of Autism Spectrum Disorder, Attention Deficit Hyperactivity Disorder, Obsessive-Compulsive Disorder, Schizophrenia or Psychotic Disorder, any type of Depressive Disorder, Anxiety Disorder, and/or Eating Disorder, as well as any Personality Disorder, and Post-Traumatic Stress Disorder were excluded from the analysis.

Supplementary Table S2. Results of the linear mixed model on log-transformed RT regarding probabilistic learning in Study 1.

<i>Terms</i>	Prediction of RT					
	<i>b</i>	<i>SE</i>	<i>95% CI</i>	<i>t</i>	<i>df</i>	<i>p</i>
(Intercept)	362.403	2.483	357.534 – 367.339	860.194	161.990	<0.001
Block 1-5 [1]	1.035	0.002	1.030 – 1.040	14.301	168.514	<0.001
Block 6-10 [2]	1.024	0.002	1.020 – 1.028	11.527	169.789	<0.001
Block 11-15 [3]	1.001	0.002	0.998 – 1.005	0.779	174.609	0.437
Block 16-20 [4]	0.979	0.002	0.975 – 0.982	-11.537	174.930	<0.001
Triplet Type [High]	0.990	0.001	0.988 – 0.991	-17.513	159.694	<0.001
OCI-R score	0.999	0.001	0.998 – 1.001	-0.976	161.987	0.330
Block 1-5 [1] x— Triplet Type [High]	1.006	0.001	1.004 – 1.007	7.169	243491.238	<0.001
Block 6-10 [2] x— Triplet Type [High]	1.002	0.001	1.001 – 1.004	3.061	243497.789	0.002
Block 11-15 [3] x— Triplet Type [High]	0.999	0.001	0.998 – 1.001	-0.886	243491.490	0.376
Block 16-20 [4] x— Triplet Type [High]	0.996	0.001	0.995 – 0.998	-4.652	243500.591	<0.001
Block 1-5 [1] x— OCI-R score	1.000	0.000	1.000 – 1.000	0.140	168.494	0.889
Block 6-10 [2] x— OCI-R score	1.000	0.000	0.999 – 1.000	-1.142	169.508	0.255
Block 11-15 [3] x— OCI-R score	1.000	0.000	1.000 – 1.000	-1.070	174.532	0.286
Block 16-20 [4] x— OCI-R score	1.000	0.000	1.000 – 1.001	2.053	174.787	0.042
Triplet Type [High] x OCI-R score	1.000	0.000	1.000 – 1.000	-0.338	159.451	0.736
(Block 1-5 [1] x— Triplet Type [High] x— OCI-R score	1.000	0.000	1.000 – 1.000	-1.822	243478.403	0.068
(Block 6-10 [2] x— Triplet Type [High] x— OCI-R score	1.000	0.000	1.000 – 1.000	2.010	243500.616	0.044
(Block 11-15 [3] x— Triplet Type [High] x— OCI-R score	1.000	0.000	1.000 – 1.000	0.648	243484.789	0.517
(Block 16-20 [4] x— Triplet Type [High] x— OCI-R score	1.000	0.000	1.000 – 1.000	-0.679	243494.478	0.497

Random Effects

σ^2	0.032
τ_{00} Participant	0.008
τ_{11} Participant.Block 1-5	0.001
τ_{11} Participant.Block 6-10	0.001
τ_{11} Participant.Block 11-15	0.000
τ_{11} Participant.Block 15-20	0.000
τ_{11} Participant. Triplet Type [High]	0.000
ρ_{01}	0.209
	0.203
	-0.133
	-0.150
	0.393
ICC	0.210
N Participant	164
Observations	244258
Marginal R^2 / Conditional R^2	0.023 / 0.228

Note. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Degrees of freedom are based on Satterthwaite's approximation. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

Supplementary Table S3. Results of the binomial generalized mixed model on accuracy regarding probabilistic learning in Study 1.

<i>Terms</i>	Prediction of Accuracy					
	<i>Log-Odds</i>	<i>SE</i>	<i>95% CI</i>	<i>z</i>	<i>df</i>	<i>p</i>
(Intercept)	2.314	0.036	2.243 – 2.385	63.864	Inf	<0.001
Block 1-5 [1]	0.137	0.025	0.089 – 0.186	5.544	Inf	<0.001
Block 6-10 [2]	0.018	0.021	-0.024 – 0.060	0.843	Inf	0.399
Block 11-15 [3]	0.017	0.020	-0.022 – 0.056	0.855	Inf	0.393
Block 16-20 [4]	-0.052	0.019	-0.090 – -0.014	-2.687	Inf	0.007
Triplet Type [High]	0.163	0.011	0.141 – 0.185	14.418	Inf	<0.001
OCI-R score	0.007	0.003	0.001 – 0.014	2.272	Inf	0.023
Block 1-5 [1] x— Triplet Type [High]	-0.061	0.015	-0.090 – -0.032	-4.106	Inf	<0.001
Block 6-10 [2] x— Triplet Type [High]	-0.002	0.014	-0.030 – 0.026	-0.167	Inf	0.867
Block 11-15 [3] x— Triplet Type [High]	-0.002	0.014	-0.030 – 0.026	-0.150	Inf	0.881
Block 16-20 [4] x— Triplet Type [High]	0.031	0.014	0.004 – 0.059	2.230	Inf	0.026

Block 1-5 [1] x— OCI-R score	-0.003	0.002	-0.007 – 0.002	-1.170	Inf	0.242
Block 6-10 [2] x— OCI-R score	0.000	0.002	-0.003 – 0.004	0.078	Inf	0.938
Block 11-15 [3] x— OCI-R score	0.000	0.002	-0.003 – 0.004	0.165	Inf	0.869
Block 16-20 [4] x— OCI-R score	0.001	0.002	-0.002 – 0.005	0.738	Inf	0.461
Triplet Type [High] x OCI-R score	0.001	0.001	-0.001 – 0.002	0.518	Inf	0.605
(Block 1-5 [1] x— Triplet Type [High] x — OCI-R score	0.001	0.001	-0.001 – 0.004	1.102	Inf	0.271
(Block 6-10 [2] x— Triplet Type [High] x — OCI-R score	-0.002	0.001	-0.004 – 0.001	-1.356	Inf	0.175
(Block 11-15 [3] x— Triplet Type [High] x — OCI-R score	-0.001	0.001	-0.003 – 0.002	-0.638	Inf	0.524
(Block 16 -20 [4] x— Triplet Type [High] x — OCI-R score	-0.001	0.001	-0.004 – 0.001	-0.928	Inf	0.353

Random Effects

σ^2	3.290
τ_{00} Participant	0.208
τ_{11} Participant.Block 1-5	0.059
τ_{11} Participant.Block 6-10	0.036
τ_{11} Participant.Block 11-15	0.027
τ_{11} Participant.Block 15-20	0.025
τ_{11} Participant. Triplet Type [High]	0.011
ρ_{01}	0.116
	0.185
	-0.079
	-0.255
	0.034
ICC	0.073
N Participant	164
Observations	269363
Marginal R ² / Conditional R ²	0.010 / 0.082

Note. The table shows regression coefficients of fixed effects and summary information about the random effects. Coefficients are log odds, thus positive values indicate that the given independent variable is associated with an increased likelihood of correct responses, and negative values are the opposite. P values for coefficients are from z tests, making the degrees of freedom infinite. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

Supplementary Table S4. Results of the linear mixed model on log-transformed RT regarding probabilistic learning in Study 2.

Terms	Prediction of RT					
	<i>b</i>	<i>SE</i>	95% <i>CI</i>	<i>t</i>	<i>df</i>	<i>p</i>

(Intercept)	381.301	2.026	377.332 – 385.313	1118.456	254.905	<0.001
Block 1-5 [1]	1.008	0.002	1.005 – 1.011	5.199	268.151	<0.001
Block 6-10 [2]	1.006	0.001	1.004 – 1.008	5.502	279.135	<0.001
Triplet Type [High]	0.993	0.001	0.992 – 0.994	-13.534	250.990	<0.001
OCI-R score	1.000	0.000	0.999 – 1.000	-0.882	254.944	0.379
Block 1-5 [1] x — Triplet Type [High]	1.002	0.001	1.001 – 1.003	3.508	227191.022	<0.001
Block 6-10 [1] x — Triplet Type [High]	1.001	0.001	0.999 – 1.002	1.090	227215.145	0.276
Block 1-5 [1] x— OCI-R score	1.000	0.000	1.000 – 1.000	-1.026	268.791	0.306
Block 6-10 [2] x— OCI-R score	1.000	0.000	1.000 – 1.000	0.764	280.900	0.446
Triplet Type [High] x— OCI-R score	1.000	0.000	1.000 – 1.000	0.453	253.339	0.651
(Block 1-5 [1] x— Triplet Type [High]) x— OCI-R	1.000	0.000	1.000 – 1.000	1.310	227196.061	0.190
(Block 6-10 [2] x— Triplet Type [High]) x— OCI-R	1.000	0.000	1.000 – 1.000	-0.813	227176.306	0.416
Random Effects						
σ^2	0.033					
τ_{00} Participant	0.007					
τ_{11} Participant, Block 1-5	0.001					
τ_{11} Participant, Block 6-10	0.000					
τ_{11} Participant, Triplet_Type[High]	0.000					
ρ_{01}	0.144					
	0.001					
	0.110					
ICC	0.191					
N Participant	257					
Observations	227889					
Marginal R^2 / Conditional R^2	0.005 / 0.195					

Note. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Degrees of freedom are based on Satterthwaite's approximation. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

Supplementary Table S5. Results of the linear mixed model on log-transformed RT regarding 'Old knowledge' in Study 2.

<i>Terms</i>	Prediction of RT					
	<i>b</i>	<i>SE</i>	<i>95% CI</i>	<i>t</i>	<i>df</i>	<i>p</i>

Prediction of RT						
(Intercept)	358.244	1.887	354.547 – 361.979	1116.469	255.225	<0.001
Block 16-20 [1]	0.978	0.002	0.975 – 0.981	-14.373	298.397	<0.001
Block 21-25 [2]	1.009	0.001	1.006 – 1.011	6.500	259.212	<0.001
Triplet Type [H L]	0.989	0.001	0.987 – 0.990	-15.801	270.983	<0.001
OCI-R score	1.000	0.000	0.999 – 1.000	-0.898	255.254	0.370
Block 16-20 [1] x— Triplet Type [H L]	1.001	0.001	1.000 – 1.003	1.570	156792.988	0.116
Block 21-25 [2] x— Triplet Type [H L]	1.000	0.001	0.998 – 1.002	0.018	156791.687	0.986
Block 16-20 [1] x— OCI-R score	1.000	0.000	0.999 – 1.000	-1.793	299.581	0.074
Block 21-25 [2] x— OCI-R score	1.000	0.000	1.000 – 1.000	1.987	260.105	0.048
Triplet Type [H L] x— OCI-R score	1.000	0.000	1.000 – 1.000	1.359	272.087	0.175
(Block 16-20 [1] x— Triplet Type [H L] x— OCI-R score)	1.000	0.000	1.000 – 1.000	-0.534	156914.412	0.593
(Block 21-25 [2] x— Triplet Type [H L] x— OCI-R score)	1.000	0.000	1.000 – 1.000	-1.000	156723.370	0.317
Random Effects						
σ^2	0.030					
τ_{00} Participant	0.007					
τ_{11} Participant Block 16-20 [1]	0.000					
τ_{11} Participant Block 21-25 [2]	0.000					
τ_{11} Participant. Triplet Type [H L]	0.000					
ρ_{01}	0.107					
	-0.046					
	0.162					
ICC	0.205					
N Participant	257					
Observations	157503					
Marginal R ² / Conditional R ²	0.011 / 0.214					

Note. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Degrees of freedom are based on Satterthwaite's approximation. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

Supplementary Table S6. Results of the binomial generalized mixed model on accuracy regarding probabilistic learning in Study 2.

Prediction of Accuracy						
Terms	Log-Odds	SE	95% CI	z	df	p

(Intercept)	2.417	0.029	2.361 – 2.474	83.993	Inf	<0.001
Block 1-5 [1]	0.145	0.019	0.108 – 0.182	7.652	Inf	<0.001
Block 6-10 [2]	-0.052	0.014	-0.080 – -0.024	-3.668	Inf	<0.001
Triplet Type [High]	0.143	0.010	0.124 – 0.161	14.997	Inf	<0.001
OCI-R score	-0.006	0.002	-0.011 – -0.001	-2.555	Inf	0.011
Block 1-5 [1] x — Triplet Type [High]	-0.042	0.011	-0.064 – -0.019	-3.672	Inf	<0.001
Block 6-10 [1] x — Triplet Type [High]	-0.008	0.011	-0.029 – 0.014	-0.703	Inf	0.482
Block 1-5 [1] x— OCI-R score	0.000	0.002	-0.003 – 0.003	0.024	Inf	0.981
Block 6-10 [2] x— OCI-R score	0.001	0.001	-0.001 – 0.003	0.683	Inf	0.495
Triplet Type [High] x— OCI-R score	-0.000	0.001	-0.002 – 0.001	-0.467	Inf	0.640
(Block 1-5 [1] x— Triplet Type [High]) x— OCI-R	-0.000	0.001	-0.002 – 0.001	-0.371	Inf	0.710
(Block 6-10 [2] x— Triplet Type [High]) x— OCI-R	0.002	0.001	0.000 – 0.004	2.445	Inf	0.014

Random Effects

σ^2	3.290
τ_{00} Participant	0.194
τ_{11} Participant, Block 1-5	0.053
τ_{11} Participant, Block 6-10	0.017
τ_{11} Participant, Triplet_Type[High]	0.006
ρ_{01}	0.351
	-0.161
	0.448
ICC	0.070
N Participant	257
Observations	249134
Marginal R ² / Conditional R ²	0.009 / 0.079

Note. The table shows regression coefficients of fixed effects and summary information about the random effects. Coefficients are log odds, thus positive values indicate that the given independent variable is associated with an increased likelihood of correct responses, and negative values are the opposite. P values for coefficients are from z tests, making the degrees of freedom infinite. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

Supplementary Table S7. Results of the binomial mixed model on accuracy regarding 'Old knowledge' in Study 2.

Terms	Prediction of Accuracy					
	Log-Odds	SE	95% CI	z	df	p
(Intercept)	2.389	0.026	2.339 – 2.440	93.505	Inf	<0.001

Block 16-20 [1]	0.062	0.018	0.026 – 0.098	3.414	Inf	0.001
Block 21-25 [2]	-0.026	0.019	-0.064 – 0.012	-1.349	Inf	0.177
Triplet Type [H L]	0.166	0.014	0.138 – 0.193	11.774	Inf	<0.001
OCI-R score	-0.002	0.002	-0.006 – 0.002	-0.938	Inf	0.348
Block 16-20 [1] x— Triplet Type [H L]	0.054	0.015	0.026 – 0.083	3.687	Inf	<0.001
Block 21-25 [2] x— Triplet Type [H L]	-0.078	0.017	-0.112 – -0.044	-4.538	Inf	<0.001
Block 16-20 [1] x— OCI-R score	-0.002	0.002	-0.005 – 0.001	-1.384	Inf	0.166
Block 21-25 [2] x— OCI-R score	0.002	0.002	-0.001 – 0.005	1.036	Inf	0.300
Triplet Type [H L] x— OCI-R score	-0.000	0.001	-0.003 – 0.002	-0.423	Inf	0.672
(Block 16-20 [1] x— Triplet Type [H L] x—OCI-R score	0.001	0.001	-0.002 – 0.003	0.481	Inf	0.630
(Block 21-25 [2] x— Triplet Type [H L] x—OCI-R score	0.001	0.001	-0.002 – 0.004	0.589	Inf	0.556
Random Effects						
σ^2	3.290					
τ_{00} Participant	0.133					
τ_{11} Participant Block 16-20 [1]	0.024					
τ_{11} Participant Block 21-25 [2]	0.012					
τ_{11} Participant. Triplet Type [H L]	0.017					
ρ_{01}	0.159					
	-0.101					
	0.108					
ICC	0.052					
N Participant.Public.ID	257					
Observations	171403					
Marginal R ² / Conditional R ²	0.008 / 0.060					

Note. The table shows regression coefficients of fixed effects and summary information about the random effects. Coefficients are log odds, thus positive values indicate that the given independent variable is associated with an increased likelihood of correct responses, and negative values are the opposite. P values for coefficients are from z tests, making the degrees of freedom infinite. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

Supplementary Table S8. Results of the linear mixed model on log-transformed RT regarding 'New knowledge' in Study 2.

<i>Terms</i>	Prediction of RT					
	<i>b</i>	<i>SE</i>	<i>95% CI</i>	<i>t</i>	<i>df</i>	<i>p</i>
(Intercept)	361.404	1.893	357.695 – 365.152	1124.232	255.210	<0.001

Block 16-20 [1]	0.979	0.001	0.976 – 0.982	-14.016	256.985	<0.001
Block 21-25 [2]	1.007	0.001	1.005 – 1.009	6.003	289.047	<0.001
Triplet Type [L H]	0.997	0.001	0.996 – 0.999	-3.501	274.785	0.001
OCI-R score	1.000	0.000	0.999 – 1.000	-0.881	255.281	0.379
Block 16-20 [1] x—Triplet Type [L H]	1.002	0.001	1.000 – 1.004	2.493	110434.011	0.013
Block 21-25 [2] x—Triplet Type [L H]	0.998	0.001	0.997 – 1.000	-2.063	110274.701	0.039
Block 16-20 [1] x— OCI-R score	1.000	0.000	1.000 – 1.000	-1.676	258.715	0.095
Block 21-25 [2] x— OCI-R score	1.000	0.000	1.000 – 1.000	2.228	291.538	0.027
Triplet Type [L H] x— OCI-R score	1.000	0.000	1.000 – 1.000	1.345	277.633	0.180
(Block 16-20 [1] x—Triplet Type [L H]) x— OCI-R score	1.000	0.000	1.000 – 1.000	-0.218	110426.496	0.827
(Block 21-25 [2] x—Triplet Type [L H]) x— OCI-R score	1.000	0.000	1.000 – 1.000	-1.284	110286.125	0.199
Random Effects						
σ^2	0.030					
τ_{00} Participant	0.007					
τ_{11} Participant Block 16-20 [1]	0.000					
τ_{11} Participant Block 21-25 [2]	0.000					
τ_{11} Participant Triplet Type [L H]	0.000					
ρ_{01}	0.151					
	-0.008					
	0.085					
ICC	0.196					
N Participant	257					
Observations	110862					
Marginal R ² / Conditional R ²	0.004 / 0.200					

Note. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Degrees of freedom are based on Satterthwaite's approximation. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level

Supplementary Table S9. Results of the binomial mixed model on accuracy regarding 'New knowledge' in Study 2.

<i>Terms</i>	Prediction of accuracy					
	<i>Log-Odds</i>	<i>SE</i>	<i>95% CI</i>	<i>z</i>	<i>df</i>	<i>p</i>

(Intercept)	2.263	0.025	2.213 – 2.313	89.472	Inf	<0.001
Block 16-20 [1]	0.008	0.022	-0.035 – 0.051	0.376	Inf	0.707
Block 21-25 [2]	0.100	0.018	0.064 – 0.135	5.457	Inf	<0.001
Triplet Type [L H]	0.035	0.013	0.009 – 0.061	2.664	Inf	0.008
OCI-R score	-0.003	0.002	-0.007 – 0.001	-1.290	Inf	0.197
Block 16-20 [1] x—Triplet Type [L H]	-0.005	0.017	-0.038 – 0.029	-0.271	Inf	0.787
Block 21-25 [2] x—Triplet Type [L H]	0.040	0.015	0.011 – 0.070	2.656	Inf	0.008
Block 16-20 [1] x— OCI-R score	-0.001	0.002	-0.005 – 0.002	-0.736	Inf	0.461
Block 21-25 [2] x— OCI-R score	0.001	0.002	-0.002 – 0.004	0.597	Inf	0.551
Triplet Type [L H] x— OCI-R score	-0.001	0.001	-0.003 – 0.001	-1.141	Inf	0.254
(Block 16-20 [1] x—Triplet Type [L H]) x— OCI-R score	0.001	0.001	-0.002 – 0.004	0.766	Inf	0.444
(Block 21-25 [2] x—Triplet Type [L H]) x— OCI-R score	0.000	0.001	-0.002 – 0.003	0.230	Inf	0.818
Random Effects						
σ^2	3.290					
τ_{00} Participant	0.126					
τ_{11} Participant Block 16-20 [1]	0.041					
τ_{11} Participant Block 21-25 [2]	0.021					
τ_{11} Participant Triplet Type [L H]	0.008					
ρ_{01}	0.235					
	-0.161					
	-0.142					
ICC	0.043					
N Participant.Public.ID	257					
Observations	122349					
Marginal R ² / Conditional R ²	0.004 / 0.047					

Note. The table shows regression coefficients of fixed effects and summary information about the random effects. Coefficients are log odds, thus positive values indicate that the given independent variable is associated with an increased likelihood of correct responses, and negative values are the opposite. P values for coefficients are from z tests, making the degrees of freedom infinite. The marginal R-squared considers only the variance of the fixed effects, while the conditional R-squared takes both the fixed and random effects into account. Statistically significant terms are highlighted in bold. Terms in brackets indicate the level of factor that is contrasted against the reference level.

9.2. Supplementary Materials of Study 3

Supplemental Information

Obsessive-Compulsive Tendencies Shift the Balance Between Competitive Neurocognitive Functions

Bianka Brezóczki, Teodóra Vékony, Bence Csaba Farkas, Flóra Hann, Dezső Németh

Supplementary Figures

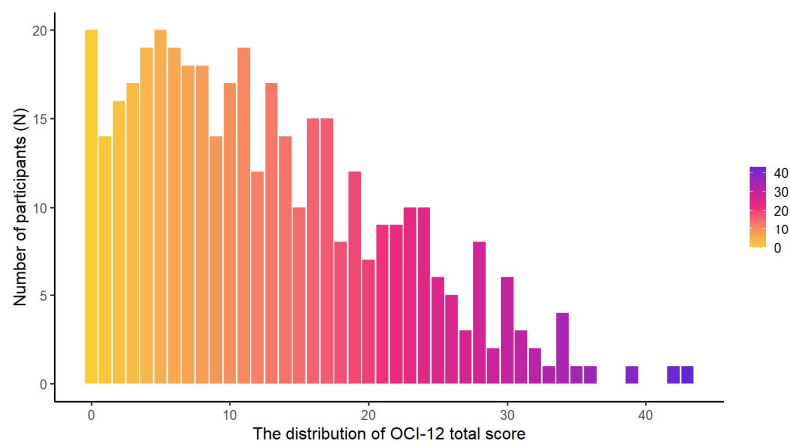


Figure S1. The distribution of the participants' OC tendencies as measured by the OCI-12 total score in the sample. The x-axis indicates the total OCI-12 score, while the y-axis indicates the number of participants. The color gradient transitions from yellow, through pink, to purple, reflecting increasing levels of OC tendencies.

Supplementary Tables

Table S1. LMM predicting blockwise median RT, Related to Results

<i>Terms</i>	Reaction Time					
	<i>b</i>	<i>SE b</i>	<i>95% CI</i>	<i>t</i>	<i>df</i>	<i>p</i>
(Intercept)	378.23	2.08	374.13 – 382.32	181.69	400.01	< 0.001
Time	-1.10	0.10	-1.29 – -0.90	-11.18	399.98	< 0.001
Triplet Type [High]	-2.94	0.23	-3.38 – -2.49	-13.01	11297.07	< 0.001
OCI-12 score	-0.42	0.23	-0.88 – 0.04	-1.77	400.01	0.077
Perseverative error	1.44	0.53	0.39 – 2.49	2.70	400.02	0.007
Time × Triplet Type [High]	-0.17	0.05	-0.27 – -0.07	-3.23	11297.10	0.001
Time × OCI-12 score	0.00	0.01	-0.02 – 0.03	0.39	399.88	0.699
Triplet Type [High] × OCI-12 score	-0.00	0.03	-0.05 – 0.05	-0.09	11297.11	0.926
Time × Perseverative error	-0.04	0.03	-0.09 – 0.00	-1.77	400.07	0.078
Triplet Type [High] × Perseverative error	-0.04	0.06	-0.15 – 0.08	-0.66	11297.07	0.508
OCI-12 score × Perseverative error	-0.03	0.06	-0.14 – 0.08	-0.52	400.01	0.600
(Time × Triplet Type [High]) × OCI-12 score	0.00	0.01	-0.01 – 0.01	0.30	11297.18	0.763
(Time × Triplet Type [High]) × Perseverative error	0.01	0.01	-0.01 – 0.04	0.96	11297.10	0.338
(Time × OCI-12 score) × Perseverative error	0.00	0.00	-0.00 – 0.01	1.90	400.00	0.058
(Triplet Type [High] × OCI-12 score) × Perseverative error	0.01	0.01	-0.00 – 0.02	1.13	11297.09	0.257
(Time × Triplet Type [High] × OCI-12 score) × Perseverative error	-0.00	0.00	-0.00 – 0.00	-0.82	11297.15	0.412
Random Effects						
σ^2	608.04					
τ_{00} Participant	1703.21					
τ_{11} Participant.Time	2.73					
ρ_{01} Participant	-0.30					
ICC	0.74					
N Participant	404					
Observations	12113					

Note. Statistical learning was evidenced by faster RTs for high-probability triplets compared to low-probability ones (main effect of Triplet Type). Reaction times improved throughout the task (main effect of Time). The interaction between Triplet Type and Block indicated that statistical learning (the difference between high- and low-probability triplets) became more pronounced as the task progressed. There was a statistically significant main effect of Perseverative Errors, indicating that more perseverative errors were associated with significantly slower reaction times. The absence of a significant interaction between Triplet Type and Perseverative Errors suggests that there is no antagonistic relationship between these factors.

Table S2. LMM predicting blockwise mean accuracy, Related to Results

<i>Terms</i>	Accuracy					
	<i>b</i>	<i>SE b</i>	<i>95% CI</i>	<i>t</i>	<i>df</i>	<i>p</i>
(Intercept)	90.90	0.17	90.56 – 91.24	525.51	400.00	<0.001
Time	-0.15	0.02	-0.18 – -0.11	-7.67	400.22	<0.001
Triplet Type [High]	1.11	0.06	0.99 – 1.24	17.40	400.14	<0.001
OCI-12 score	-0.00	0.02	-0.04 – 0.04	-0.03	399.97	0.976
Perseverative error	-0.11	0.04	-0.20 – -0.02	-2.49	400.06	0.013
Time × Triplet Type [High]	0.08	0.01	0.05 – 0.11	5.76	10898.51	<0.001
Time × OCI-12 score	-0.00	0.00	-0.00 – 0.00	-0.08	400.05	0.935
Triplet Type [High] × OCI-12 score	0.01	0.01	-0.01 – 0.02	0.94	399.91	0.347
Time × Perseverative error	-0.01	0.00	-0.02 – -0.00	-2.10	400.39	0.036
Triplet Type [High] × Perseverative error	0.03	0.02	0.00 – 0.07	2.12	400.52	0.035
OCI-12 score × Perseverative error	-0.00	0.00	-0.01 – 0.00	-0.95	400.03	0.341
(Time × Triplet Type [High]) × OCI-12 score	-0.00	0.00	-0.00 – 0.00	-0.99	10898.03	0.321
(Time × Triplet Type [High]) × Perseverative error	-0.00	0.00	-0.01 – 0.01	-0.20	10899.01	0.845
(Time × OCI-12 score) × Perseverative error	0.00	0.00	-0.00 – 0.00	1.52	400.26	0.130
(Triplet Type [High] × OCI-12 score) × Perseverative error	-0.00	0.00	-0.01 – -0.00	-2.49	400.30	0.013
(Time × Triplet Type [High]) × OCI-12 score × Perseverative error	-0.00	0.00	-0.00 – 0.00	-1.35	10898.65	0.178
Random Effects						
σ^2	41.20					
τ_{00} Participant	10.53					

τ_{11} Participant.Time	0.07
τ_{11} Participant.Triplet Type [High]	0.25
ρ_{01}	-0.05
	-0.69
ICC	0.23
N Participant	404
Observations	12113
Marginal R^2 / Conditional R^2	0.036 / 0.255

Note. Statistical learning was evidenced by higher accuracy for high-probability triplets compared to low-probability ones (main effect of Triplet Type). Accuracy declined over the course of the task (main effect of Block). The interaction between Triplet Type and Block indicated increasing statistical learning (the difference between high- and low-probability triplets) as the task progressed. A statistically significant main effect of Perseverative Errors suggested that higher perseverative error rates were associated with lower response accuracy, accompanied by a decline in visuomotor performance as the task progressed (Time $\times$ Perseverative error interaction). A significant interaction between Triplet Type and Perseverative Errors indicated an antagonistic relationship between statistical learning and cognitive flexibility. The significant Triplet Type $\times$ Perseverative Errors $\times$ OCI-R score interaction revealed that OC tendencies modulate this antagonistic relationship.

Table S3. LMM predicting blockwise median RT, Related to Results

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time	1, 399.99	120.03	< . .001
Triplet Type	1, 11297.08	168.31	< . .001
OCI-12 score	1, 400.00	2.44	.119
Trials to complete first category	1, 400.00	1.26	.263
Time $\times$ Triplet Type	1, 11297.13	11.08	< . .001
Time $\times$ OCI-12 score	1, 399.88	0.28	.595
Triplet Type $\times$ OCI-12 score	1, 11297.1	0.02	.904
Time $\times$ Trials to complete first category	1, 399.83	0.23	.635
Triplet Type $\times$ Trials to complete first category	1, 11297.04	0.20	.652
OCI-12 score $\times$ Trials to complete first category	1, 400.00	0.02	.887
Time $\times$ Triplet Type $\times$ OCI-12 score	1, 11297.15	0.07	.790
Time $\times$ Triplet Type $\times$ Trials to complete first category	1, 11297.05	0.56	.454
Time $\times$ OCI-12 score $\times$ Trials to complete first category	1, 399.80	0.06	.801
Triplet Type $\times$ OCI-12 score $\times$ Trials to complete first category	1, 11297.04	0.23	.632

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time × Triplet Type × OCI-12 score × Trials to complete first category	1, 11297.05	0.11	.738

Note. The table summarizes all main effects and interactions. Degrees of freedom (*df*) correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results (*p* < .05) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type (High vs. Low) was significant (*b* = -5.82, SE = 0.449, *z* = -12.973, *p* < .0001), indicating faster responses to high- than to low-probability triplets. Time was also significant (*b* = -1.07, SE = 0.0981, *z* = -10.956, *p* < .0001, 95% CI [-1.27, -0.882]), indicating that RT decreased as the task progressed. The Time × Triplet Type interaction was also significant (*b* = -0.346, SE = 0.104, *z* = -3.329, *p* = .0009), indicating a stronger decrease in RT for high-probability triplets over time. To depict the interaction, time was divided into three blocks (Block₅, Block₁₀, Block₁₅). Pairwise comparisons showed significant High–Low differences at Block₅ (*b* = -4.79, SE = 0.547, 95% CI [-5.86, -3.71]), Block₁₀ (*b* = -6.52, SE = 0.495, 95% CI [-7.48, -5.55]), and Block₁₅ (*b* = -8.24, SE = 0.855, 95% CI [-9.92, -6.57]). Sidak-adjusted comparisons indicated that the High–Low difference increased significantly across time: Block₅–Block₁₀ (*b* = 1.73, SE = 0.52, *z* = 3.329, *p* = .0026), Block₅–Block₁₅ (*b* = 3.46, SE = 1.04, *z* = 3.329, *p* = .0026), and Block₁₀–Block₁₅ (*b* = 1.73, SE = 0.52, *z* = 3.329, *p* = .0026). These results indicate a gradual increase in statistical learning across the task.

Table S4. LMM predicting blockwise mean accuracy, Related to Results

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time	1, 400.25	55.48	< .001
Triplet Type	1, 399.97	288.22	< .001
OCI-12 score	1, 399.96	0.57	.450
Trials to complete first category	1, 399.94	0.22	.639
Time × Triplet Type	1, 10898.42	31.05	< .001
Time × OCI-12 score	1, 400.08	0.05	.824
Triplet Type × OCI-12 score	1, 399.77	1.10	.295
Time × Trials to complete first category	1, 399.98	1.55	.214
Triplet Type × Trials to complete first category	1, 399.66	0.17	.680
OCI-12 score × Trials to complete first category	1, 399.94	2.18	.141
Time × Triplet Type × OCI-12 score	1, 10897.91	1.3	.255
Time × Triplet Type × Trials to complete first category	1, 10897.59	0.58	.446
Time × OCI-12 score × Trials to complete first category	1, 399.94	0.52	.470
Triplet Type × OCI-12 score × Trials to complete first category	1, 399.62	4.58	.033
Time × Triplet Type × OCI-12 score × Trials to complete first category	1, 10897.47	0.77	.379

Note. The table summarizes all main effects and interactions. Degrees of freedom (*df*) correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results (*p* <

.05) are shown in bold. Significant main effects were followed up with post hoc comparisons. The main effect of Triplet Type (High vs. Low) was significant ($b = 2.17$, $SE = 0.128$, $z = 16.977$, $p < .0001$), indicating higher accuracy for high- than for low-probability triplets. The linear trend of Time was also significant ($b = -0.141$, $SE = 0.0189$, $z = -7.448$, $p < .0001$, 95% CI [-0.178, -0.104]), indicating that accuracy decreased as the task progressed. To depict the Time $\times$ Triplet Type interaction, time was segmented into three blocks (Block₅, Block₁₀, Block₁₅). Pairwise comparisons showed significant High–Low differences at Block₅ ($b = 1.72$, $SE = 0.151$, 95% CI [1.42, 2.01]), Block₁₀ ($b = 2.47$, $SE = 0.139$, 95% CI [2.20, 2.74]), and Block₁₅ ($b = 3.22$, $SE = 0.228$, 95% CI [2.78, 3.67]). Sidak-adjusted comparisons indicated that the High–Low difference increased significantly across time: Block₅–Block₁₀ ($b = -0.754$, $SE = 0.135$, $z = -5.572$, $p < .0001$), Block₅–Block₁₅ ($b = -1.507$, $SE = 0.270$, $z = -5.572$, $p < .0001$), and Block₁₀–Block₁₅ ($b = -0.754$, $SE = 0.135$, $z = -5.572$, $p < .0001$), indicating increasing statistical learning over time. The significant three-way interaction, we examined the simple effect of triplet type (high- vs. low-probability triplets) at -1 SD, mean, and $+1$ SD levels of Trials to complete the first category and OCI-12 scores. Please note that, we used the OCI-12 score and the Trials to complete the first category as a continuous variable for all our analyses; we only depicted results for post-hoc analysis. Among individuals with low OC tendencies, the SL performance decreased as the number of trials to complete the first category increased. When participants completed the first category quickly, the statistical learning was largest, $b = 2.42$, $SE = 0.26$, $z = 9.17$, 95% CI [1.90, 2.94], $p < .001$. At the mean level of trials, the effect was smaller, $b = 2.03$, $SE = 0.18$, $z = 11.16$, 95% CI [1.68, 2.39], $p < .001$, and it was smallest at later trials, $b = 1.65$, $SE = 0.30$, $z = 5.48$, 95% CI [1.06, 2.24], $p < .001$. At a medium OC tendencies, statistical remained relatively stable across levels of trials ($b_{\text{earlier trials}} = 2.22$; $b_{\text{mean trials}} = 2.17$; $b_{\text{later trials}} = 2.11$; all $ps < .001$), suggesting little modulation of statistical learning by cognitive flexibility. In contrast, among individuals with higher OC tendencies, the pattern reversed. The triplet effect increased as trials to complete the first category increased. At earlier trials, the effect was $b = 2.02$, $SE = 0.26$, $z = 7.86$, 95% CI [1.52, 2.53], $p < .001$; at mean trials, $b = 2.30$, $SE = 0.18$, $z = 12.75$, 95% CI [1.95, 2.66], $p < .001$; and at later trials, the effect was strongest, $b = 2.58$, $SE = 0.26$, $z = 9.84$, 95% CI [2.07, 3.10], $p < .001$. This indicates that among individuals with higher OC tendencies, poorer CST performance was associated with enhanced statistical learning.

Table S5. LMM predicting blockwise median RT, Related to Results

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time	1, 399.95	127.73	< . .001
Triplet Type	1, 11297.06	170.45	< . .001
OCI-12 score	1, 400.00	4.66	.032
Total correct	1, 400.01	12.55	< . .001
Time $\times$ Triplet Type	1, 11297.08	9.73	.002
Time $\times$ OCI-12 score	1, 399.87	0.25	.615
Triplet Type $\times$ OCI-12 score	1, 11297.0917	0.00	.960
Time $\times$ Total correct	1, 400.01	2.21	.138
Triplet Type $\times$ Total correct	1, 11297.10	0.27	.607
OCI-12 score $\times$ Total correct	1, 400.00	0.10	.750
Time $\times$ Triplet Type $\times$ OCI-12 score	1, 11297.15	0.15	.698
Time $\times$ Triplet Type $\times$ Total correct	1, 11297.17	0.00	.952
Time $\times$ OCI-12 score $\times$ Total correct	1, 399.96	6.02	.015

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Triplet Type × OCI-12 score × Total correct	1, 11297.14	2.55	.110
Time × Triplet Type × OCI-12 score × Total correct	1, 11297.23	1.36	.244

Note. The table summarizes all main effects and interactions. Degrees of freedom (*df*) correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results (*p* < .05) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type (High vs. Low) was significant (*b* = -5.93, SE = 0.454, *z* = -13.056, *p* < .0001), indicating faster responses to high- than to low-probability triplets. The linear trend of Time was also significant (*b* = -1.11, SE = 0.0984, *z* = -11.302, *p* < .0001, 95% CI [-1.31, -0.92]), showing that RT decreased as the task progressed. The Time × Triplet Type interaction was significant (*b* = -0.328, SE = 0.105, *z* = -3.120, *p* = .0018), indicating a stronger decrease in RT for high-probability triplets over time. To illustrate this interaction, time was depicted at three blocks (Block₅, Block₁₀, Block₁₅). Pairwise comparisons showed significant High–Low differences at Block₅ (*b* = -4.95, SE = 0.553, 95% CI [-6.03, -3.86]), Block₁₀ (*b* = -6.59, SE = 0.501, 95% CI [-7.57, -5.60]), and Block₁₅ (*b* = -8.23, SE = 0.865, 95% CI [-9.92, -6.53]). Sidak-adjusted comparisons indicated that the High–Low difference increased significantly across time: Block₅–Block₁₀ (*b* = 1.64, SE = 0.526, *z* = 3.120, *p* = .0054), Block₅–Block₁₅ (*b* = 3.28, SE = 1.050, *z* = 3.120, *p* = .0054), and Block₁₀–Block₁₅ (*b* = 1.64, SE = 0.526, *z* = 3.120, *p* = .0054), suggesting a gradual increase in statistical learning during the task. Furthermore, there was a significant negative main effect of OCI-12 on median RT, *b* = -0.498, SE = 0.231, 95% CI [-0.95, -0.046], indicating that higher OCI-12 scores were associated with faster reaction times. Over time, the number of correct responses, and the level of OCI tendencies, RT decreased with later blocks (learning effect; *b*s ~380 ms in early blocks vs. ~376 ms in late blocks), were slightly faster for correct responses (~2 ms difference), and were faster for participants with higher OCI-12 scores (~2–3 ms faster from low to high OCI-12), with minimal evidence for a strong three-way interaction (*p* < .001).

Table S6. LMM predicting blockwise mean accuracy, Related to Results

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time	1, 400.20	60.15	< . .001
Triplet Type	1, 400.09	294.22	< . .001
OCI-12 score	1, 399.97	0.01	.906
Total correct	1, 400.02	4.01	. .046
Time × Triplet Type	1, 10,898.40	34.78	< . .001
Time × OCI-12 score	1, 400.05	0.00	.988
Triplet Type × OCI-12 score	1, 399.90	0.30	.582
Time × Total correct	1, 400.30	2.62	.106
Triplet Type × Total correct	1, 400.20	4.58	. .033
OCI-12 score × Total correct	1, 400.00	0.79	.375
Time × Triplet Type × OCI-12 score	1, 10897.99	1.19	.275
Time × Triplet Type × Total correct	1, 10898.73	0.04	.847
Time × OCI-12 score × Total correct	1, 400.22	3.88	. .050
Triplet Type × OCI-12 score × Total correct	1, 400.11	2.07	.151

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time × Triplet Type × OCI-12 score × Total correct	1, 10898.51	4.31	.038

Note. The table summarizes all main effects and interactions. Degrees of freedom (*df*) correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results (*p* < .05) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type (High vs. Low) was significant ($b = 2.21$, $SE = 0.129$, $z = 17.153$, $p < .0001$), indicating higher accuracy for high- than for low-probability triplets. The linear trend of Time was also significant ($b = -0.148$, $SE = 0.019$, $z = -7.755$, $p < .0001$, 95% CI $[-0.185, -0.110]$), showing that accuracy decreased as the task progressed. The Time × Triplet Type interaction indicated that the High–Low difference increased across time. To illustrate this interaction, time was depicted at three blocks (Block₅, Block₁₀, Block₁₅). Pairwise comparisons at three representative blocks showed significant High–Low differences at Block₅ ($b = 1.73$, $SE = 0.153$, 95% CI $[1.43, 2.03]$), Block₁₀ ($b = 2.54$, $SE = 0.140$, 95% CI $[2.26, 2.81]$), and Block₁₅ ($b = 3.34$, $SE = 0.231$, 95% CI $[2.89, 3.80]$). Šidák-adjusted comparisons confirmed that the High–Low difference increased significantly across blocks: Block₅–Block₁₀ ($b = 0.807$, $SE = 0.137$, $z = -5.898$, $p < .0001$), Block₅–Block₁₅ ($b = 1.614$, $SE = 0.274$, $z = -5.898$, $p < .0001$), and Block₁₀–Block₁₅ ($b = 0.807$, $SE = 0.137$, $z = -5.898$, $p < .0001$). The overall linear trend for correct performance was significant ($b = 0.0371$, $SE = 0.0185$, $z = 2.002$, 95% CI $[0.0008, 0.0735]$, $p = 0.045$), indicating that higher numbers of correct responses were associated with more accurate responses. The Triplet Type × Correct responses interaction revealed decreasing statistical learning with increased rate of correct responses ($b_{\text{Less correct}} = 2.24\%$, 95% CI $[1.99, 2.50]$), mean ($b_{\text{Mean correct}} = 2.21\%$, 95% CI $[1.96, 2.47]$), and ($b_{\text{More correct}} = 2.19\%$, 95% CI $[1.93, 2.44]$) (all $p < .0001$). The four-way interaction indicated that the block-related accuracy decline was driven exclusively by low-probability (L) triplets, whereas high-probability (H) triplets remained stable across blocks. This pattern was consistent across OCI-12 and correctness levels, suggesting limited moderation of temporal learning dynamics by OC tendencies or response accuracy.

Table S7. LMM predicting blockwise median RT, Related to Results

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time	399.9713	124.248	< .001
Triplet Type	11,297.0703	169.367	< .001
OCI-R score	400.0016	6.314	.012
Perseverative error	400.0107	7.197	.008
Time × Triplet Type	11,297.1001	10.343	.001
Time × OCI-R score	399.9023	1.047	.307
Triplet Type × OCI-R score	11,297.1190	0.003	.959
Time × Perseverative error	400.0583	3.242	.073
Triplet Type × Perseverative error	11,297.0705	0.497	.481
OCI-R score × Perseverative error	400.0054	0.036	.851
Time × Triplet Type × OCI-R score	11,297.1940	0.000	.985
Time × Triplet Type × Perseverative error	11,297.1004	0.990	.320
Time × OCI-R score × Perseverative error	399.9603	2.503	.114
Triplet Type × OCI-R score × Perseverative error	11,297.1020	1.491	.222

Effect	<i>df</i>	<i>F</i>	<i>p</i>
Time × Triplet Type × OCI-R score × Perseverative error	11,297.1611	0.653	.419

Note. The table summarizes all main effects and interactions. Degrees of freedom (*df*) correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results (*p* < .05) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type (High vs. Low) was significant (*b* = -5.89, *SE* = 0.452, *z* = -13.014, *p* < .0001), indicating faster responses to high-probability triplets. The main effect of Time indicated a decrease in RTs throughout the task, demonstrating changes in visuomotor performance over time (*b* = -1.09, 95% CI = [-1.29, -.90]). The Time x Triplet Type interaction was examined at three representative blocks (Block₅, Block₁₀, Block₁₅). Pairwise comparisons showed significant statistical learning Block₅ (*b* = -4.88, *SE* = 0.551, 95% CI [-5.95, -3.80]), Block₁₀ (*b* = -6.56, *SE* = 0.498, 95% CI [-7.54, -5.58]), and Block₁₅ (*b* = -8.24, *SE* = 0.861, 95% CI [-9.93, -6.55]), indicating that the High-Low RT advantage increased across time. Šidák-adjusted interaction contrasts confirmed that the statistical increased significantly over blocks: Block₅-Block₁₀ (*b* = 1.68, *SE* = 0.523, *z* = 3.216, *p* = .0039), Block₅-Block₁₅ (*b* = 3.37, *SE* = 1.050, *z* = 3.216, *p* = .0039), and Block₁₀-Block₁₅ (*b* = 1.68, *SE* = 0.523, *z* = .0039), suggesting a gradual strengthening of learning-related performance improvement over time. main effect of Perseverative error indicating that weaker cognitive flexibility (more perseverative errors) was associated with significantly slower reaction times (*b* = 1.31, 95% CI = [0.38, 2.24]).). Furthermore, the main effect of OCI-R score was statistically significant indicating faster reaction times with higher levels of OC tendencies (*b* = -0.44, 95% CI = [-0.74, -0.12]).

Table S8. LMM predicting blockwise median RT, Related to Results

<i>Terms</i>	Reaction Time					
	<i>b</i>	<i>SE b</i>	<i>95% CI</i>	<i>t</i>	<i>df</i>	<i>p</i>
(Intercept)	378.04	2.08	373.95 – 382.12	181.93	400.01	<0.001
Time	-1.09	0.10	-1.29 – -0.90	-11.15	399.97	<0.001
Triplet Type [High]	-2.94	0.23	-3.39 – -2.50	-13.01	11297.07	<0.001
OCI-R score	-0.45	0.18	-0.80 – -0.10	-2.51	400.00	0.012
Perseverative error	1.43	0.53	0.38 – 2.48	2.68	400.01	0.008
Time × Triplet Type [High]	-0.17	0.05	-0.27 – -0.07	-3.22	11297.10	0.001
Time × OCI-R score	0.01	0.01	-0.01 – 0.03	1.02	399.90	0.307
Triplet Type [High] × OCI-R score	0.00	0.02	-0.04 – 0.04	0.05	11297.12	0.959
Time × Perseverative error	-0.05	0.03	-0.09 – 0.00	-1.80	400.06	0.073
Triplet Type [High] × Perseverative error	-0.04	0.06	-0.15 – 0.07	-0.71	11297.07	0.481
OCI-R score × Perseverative error	0.01	0.04	-0.07 – 0.09	0.19	400.01	0.851
(Time × Triplet Type [High]) × OCI-R score	0.00	0.00	-0.01 – 0.01	0.02	11297.19	0.985
(Time × Triplet Type [High]) × Perseverative error	0.01	0.01	-0.01 – 0.04	1.00	11297.10	0.320
(Time × OCI-R score) × Perseverative error	0.00	0.00	-0.00 – 0.01	1.58	399.96	0.114
(Triplet Type [High] × OCI-R score) × Perseverative error	0.01	0.00	-0.00 – 0.01	1.22	11297.10	0.222
(Time × Triplet Type [High] × OCI-R score) × Perseverative error	-0.00	0.00	-0.00 – 0.00	-0.81	11297.16	0.419
Random Effects						
σ^2	608.03					
τ_{00} Participant	1692.42					
τ_{11} Participant.Time	2.73					
ρ_{01} Participant	-0.30					
ICC	0.74					
N Participant	404					
Observations	12113					
Marginal R ² / Conditional R ²	0.034 / 0.750					

Note. Statistical learning was evidenced by faster RTs for high-probability triplets compared to low-probability ones (main effect of Triplet Type). Reaction times improved throughout the task (main effect of Time). The interaction between Triplet Type and Block indicated that statistical learning (the difference between high- and low-probability triplets) became more pronounced as the task progressed. There was a

statistically significant main effect of Perseverative Errors, indicating that more perseverative errors were associated with significantly slower reaction times. The absence of a significant interaction between Triplet Type and Perseverative Errors suggests that there is no antagonistic relationship between these factors.

Table S9. LMM predicting blockwise mean accuracy, Related to Results

<i>Effect</i>	<i>df</i>	<i>F</i>	<i>p</i>
Time	1, 400.22	56.95	< . .001
Triplet Type	1, 400.12	300.37	< . .001
OCI-R score	1, 399.97	0.17	.685
Perseverative error	1, 400.06	5.89	.016
Time × Triplet Type	1, 10898.47	33.1	< . .001
Time × OCI-R score	1, 400.10	0.25	.616
Triplet Type × OCI-R score	1, 399.92	0.32	.571
Time × Perseverative error	1, 400.38	3.99	.046
Triplet Type × Perseverative error	1, 400.47	4.42	.036
OCI-R score × Perseverative error	1, 400.01	0.88	.349
Time × Triplet Type × OCI-R score	1, 10898.15	0.72	.395
Time × Triplet Type × Perseverative error	1, 10898.93	0.05	.829
Time × OCI-R score × Perseverative error	1, 400.21	0.45	.502
Triplet Type × OCI-R score × Perseverative error	1, 400.15	4.92	.027
Time × Triplet Type × OCI-R score × Perseverative error	1, 10898.44	1.6	.207

Note. The table summarizes all main effects and interactions. Degrees of freedom (*df*) correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results (*p* < .05) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type was significant (*b* = 2.22, *SE* = 0.128, *z* = 17.331, *p* < .0001), indicating higher accuracy for high- than for low-probability triplets. Pairwise comparisons showed a significant High–Low difference (*b* = –5.89, *SE* = 0.452, *z* = –13.014, *p* < .0001). The High–Low accuracy difference increased across time blocks, with significant differences at Block5 (*b* = 1.75, *SE* = 0.152, 95% CI [1.45, 2.05]), Block10 (*b* = 2.54, *SE* = 0.139, 95% CI [2.26, 2.81]), and Block15 (*b* = 3.32, *SE* = 0.230, 95% CI [2.87, 3.77]). Šidák-adjusted interaction contrasts indicated that the High–Low difference increased significantly across blocks (Block5–Block10: *b* = 0.784, *SE* = 0.136, *z* = –5.753, *p* < .0001; Block5–Block15: *b* = 1.568, *SE* = 0.273, *z* = –5.753, *p* < .0001; Block10–Block15: *b* = 0.784, *SE* = 0.136, *z* = –5.753, *p* < .0001). Perseverative error tendency showed a significant negative association with accuracy (trend estimate = –0.108, *SE* = 0.044, asymp. 95% CI [–0.195, –0.021]). Triplet Type * Perseverative error interaction demonstrated an antagonistic relationship between statistical learning and cognitive flexibility, with greater statistical learning linked to reduced cognitive flexibility (higher number of perseverative errors). (*b*_{Low Perseverative errors} = 1.95, 95% CI = [1.59, 2.30]; *b*_{Mean Perseverative errors} = 2.22, 95% CI = [1.97, 2.47]; *b*_{High Perseverative errors} = 2.50, 95% CI = [2.13, 2.86]). Triplet Type * Perseverative error * OCI-R score (*F*(1, 400.15) = 4.92, *p* = .027) highlighted the modulating role of OC tendencies in the antagonistic relationship between statistical learning and cognitive flexibility (Figure. 4). The typical antagonistic relationship between cognitive flexibility and statistical learning, where poorer flexibility is associated with enhanced statistical

learning, was observed in individuals with lower and medium OC tendencies. Please note that, we used the OCI-R score as a continuous variable for all our analyses, for post-hoc analysis, we depicted results at lower OC tendencies (Mean OCI-R score - SD), medium OC tendencies (Mean OCI-R score) and higher OC tendencies (Mean OCI-R score + SD), based on standard deviations from the mean. For lower OC tendencies, statistical learning (High – Low difference) was smallest at a low number of perseverative errors ($b_{\text{low perseverative errors}} = 1.60$, 95% CI [1.10, 2.11]), increased at mean perseverative errors ($b_{\text{Mean Perseverative errors}} = 2.15$, 95% CI [1.79, 2.50]), and was largest at high perseverative errors ($b_{\text{High Perseverative errors}} = 2.69$, 95% CI [2.16, 3.22]). For medium OC tendencies, the corresponding differences were $b_{\text{Low Perseverative errors}} = 1.95$, 95% CI [1.59, 2.30]; $b_{\text{Mean Perseverative errors}} = 2.22$, 95% CI [1.97, 2.47]; and $b_{\text{High Perseverative errors}} = 2.50$, 95% CI [2.13, 2.86]. However, this relationship weakened in individuals with high OC tendencies: $b_{\text{Low Perseverative errors}} = 2.29$, 95% CI [1.76, 2.82]; $b_{\text{Mean Perseverative errors}} = 2.30$, 95% CI [1.93, 2.66]; and $b_{\text{High Perseverative errors}} = 2.30$, 95% CI [1.88, 2.73]. Overall, the difference between high and low triplet conditions increased with higher perseverative errors under lower OC tendencies but remained relatively stable when OC tendencies were high. With higher OC tendencies, statistical learning was not enhanced in individuals with poor cognitive flexibility; instead, learning remained at a modest level, regardless of their cognitive flexibility performance.

Table S10. LMM predicting blockwise mean accuracy, Related to Results

Terms	Accuracy					
	<i>b</i>	<i>SE b</i>	95% CI	<i>t</i>	<i>df</i>	<i>p</i>
(Intercept)	90.90	0.17	90.56 – 91.24	524.99	400.01	<0.001
Time	-0.14	0.02	-0.18 – -0.12	-7.57	400.22	<0.001
Triplet Type [High]	1.11	0.06	0.99 – 1.2	17.33	400.12	<0.001
OCI-R score	-0.01	0.01	-0.04 – 0.02	-0.41	399.97	0.685
Perseverative error	-0.11	0.04	-0.2 – -0.02	-2.43	400.06	0.016
Time × Triplet Type [High]	0.08	0.01	0.05 – 0.11	5.75	10898.47	<0.001
Time × OCI-R score	0.00	0.00	-0.00 – 0.00	0.50	400.10	0.616
Triplet Type [High] × OCI-R score	0.00	0.01	-0.01 – 0.01	0.57	399.92	0.571
Time × Perseverative error	-0.01	0.00	-0.02 – -0.00	-1.99	400.38	0.046
Triplet Type [High] × Perseverative error	0.03	0.02	0.00 – 0.07	2.10	400.47	0.036
OCI-R score × Perseverative error	-0.00	0.00	-0.01 – 0.00	-0.94	400.01	0.349
(Time × Triplet Type [High]) × OCI-R score	-0.00	0.00	-0.00 – 0.00	-0.85	10898.15	0.395
(Time × Triplet Type [High]) × Perseverative error	-0.00	0.00	-0.01 – 0.01	-0.22	10898.93	0.829
(Time × OCI-R score) × Perseverative error	0.00	0.00	-0.00 – 0.00	0.67	400.21	0.502
(Triplet Type [High] × OCI-R score) × Perseverative error	-0.00	0.00	-0.01 – -0.00	-2.22	400.15	0.027
(Time × Triplet Type [High]) × OCI-R score × Perseverative error	-0.00	0.00	-0.00 – 0.00	-1.26	10898.44	0.207
Random Effects						
σ^2	41.21					
τ_{00} Participant	10.52					

τ_{11} Participant.Time	0.07
τ_{11} Participant.Time.Triplet Type	0.26
ρ_{01}	-0.05
	-0.68
ICC	0.23
N Participant	404
Observations	12113
Marginal R^2 / Conditional R^2	0.036 / 0.255

Note. Statistical learning was evidenced by higher accuracy for high-probability triplets compared to low-probability ones (main effect of Triplet Type). Accuracy declined over the course of the task (main effect of Time). The interaction between Triplet Type and Time indicated increasing statistical learning (the difference between high- and low-probability triplets) as the task progressed. A statistically significant main effect of Perseverative Errors suggested that higher perseverative error rates were associated with lower response accuracy, accompanied by a decline in visuomotor performance as the task progressed. A significant Triplet Type and Perseverative Errors interaction indicated an antagonistic relationship between statistical learning and cognitive flexibility. The significant Triplet Type $\times$ Perseverative Errors $\times$ OCI-R score interaction revealed that OC tendencies modulate this antagonistic relationship.