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Theses of the Doctoral Dissertation

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**NEUROCOGNITIVE MECHANISMS ACROSS THE SPECTRUM OF
OBSESSIVE-COMPULSIVE TENDENCIES: THE ROLE OF
STATISTICAL LEARNING**

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I. General introduction

Obsessive-Compulsive Disorder: Clinical characteristics

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). 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, 2022).

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). 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). These limitations have led to increasing interest in dimensional approaches, which conceptualize psychopathology as varying along a continuum rather than exclusively as discrete categories (Abramowitz et al., 2014; Fullana et al., 2010; Mataix-Cols et al., 2005). Within a dimensional approach, a spectrum perspective considers psychopathological characteristics across their full range of severity, including both clinical and non-clinical levels (Fullana et al., 2010; Mataix-Cols et al., 2005). Building on these conceptual advances, the present work adopts a spectrum-based approach to OCD, viewing OC tendencies as continuously varying characteristics rather than as phenomena confined to a diagnostic category.

Within this approach, a key question is how cognitive and neurocognitive functioning relates to variation in OC tendencies. 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 et al., 2011, 2014, 2015; 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., 2015, 2024; Gillan et al., 2011, 2014; Yu et al., 2024). On the other hand, complementary lines of research have implicated the role of implicit learning and memory processes in OCD symptomatology (Deckersbach et al., 2002; Exner et al., 2014; Goldman et al., 2008; Hansmeier et al., 2018; Kelmendi et al., 2016; Marker et al., 2006; Soref et al., 2018; Vloet et al., 2010; Zetsche et al., 2015). In the following sections, these two lines of research are considered within the framework of supervised and unsupervised learning, respectively.

Supervised learning

Supervised learning refers broadly to learning processes 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).

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). In contrast, habitual behavior traditionally emerges through repeated reinforcement and gradually becomes insensitive to outcome value (Balleine & O'Doherty, 2010; Carden & Wood, 2018; 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 et al., 2011, 2015; Robbins et al., 2019). 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). Studies have generally found intact performance in OCD, with some evidence of impairments in specific subgroups (Exner et al., 2014; Hansmeier et al., 2018; Kelmendi et al., 2016; Zetsche et al., 2015).

Since performance in supervised tasks depends on external feedback or reinforcement, it reflects both the acquisition of associations and the processing of their outcomes. Thus, behavioral differences observed in supervised learning paradigms can not necessarily be attributed to associative learning itself, as they may also reflect variation in feedback, reward, or outcome processing, which requires further investigation.

Unsupervised learning

In contrast, unsupervised learning occurs without explicit feedback or reinforcement, allowing regularities to be acquired directly from environmental input (Aslin, 2017; Castro et al., 2018; Conway, 2020; Love, 2002; Zhong et al., 2025). Such 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). 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; Horváth et al., 2022; Pedraza et al., 2024; Theeuwes et al., 2022).

Empirical investigations of unsupervised learning mechanisms have commonly relied on visuomotor learning paradigms, particularly the Serial Reaction Time (SRT) task (Nissen & Bullemer, 1987). Studies employing deterministic SRT paradigms have mostly reported impaired or reduced performance in OCD (Deckersbach et al., 2002; Goldman et al., 2008; Kathmann et al., 2005; Marker et al., 2006; Soref 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. 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. Despite its fundamental role, unsupervised probabilistic learning remains largely unexplored in OCD.

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. 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., 2008, 2018, 2021). Together, these theoretical and methodological challenges motivate the use of a probabilistic paradigm that can more selectively capture implicit SL while separating learning-specific effects from general visuomotor confounds.

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 task (ASRT, Farkas et al., 2023; Howard & Howard, 1997) 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 and allows for a more selective assessment of implicit SL (Horváth et al., 2022; Vékony et al., 2022). Importantly, among SL paradigms, it provides a relatively process-pure measure of probabilistic learning, capturing learning mechanisms with minimal contamination from non-learning processes (Janacek 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.

However, understanding adaptive behaviour requires considering not only the acquisition of environmental regularities, but also how previously acquired representations are modified when those regularities change. 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). 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). 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, probabilistic learning.

At what cost? - an interactive memory systems framework

Beyond the acquisition and updating of statistical regularities, adaptive behavior also depends on how automatic learning processes interact with goal-directed executive control. SL and the updating of predictive representations can not 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 et al., 2025). In this context, adaptive behaviour depends on the flexible balance between automatic and goal-directed behaviour. 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 (Ambrus et al., 2020; Horváth et al., 2025; Pedraza et al., 2024; Smalle et al., 2022).

Investigating the relationship between EF and SL in OCD, therefore, requires considering which components of executive control may be particularly relevant to the disorder. Importantly, 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). Cognitive flexibility 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 (Diamond, 2013; Miyake et al., 2000). This alteration 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.

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.

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

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

Publication:

Brezóczki, B., Vékony, T., Pesthy, O., Tóth-Fáber, E., Csigó, K., Farkas, K., & Nemeth, D. (2023). Unraveling sequence learning in obsessive–compulsive disorder. *Current Opinion in Behavioral Sciences*, 54, 101326. <https://doi.org/10.1016/j.cobeha.2023.101326>

Neurobiological models of obsessive–compulsive disorder

Current neurobiological models of OCD emphasize structural and functional alterations in the frontostriatal regions, including the putamen (Choi et al., 2007; Luo et al., 2019; Pujol et al., 2004; Radua et al., 2010; Tao et al., 2023; Zarei et al., 2011), the caudate nuclei (Choi et al., 2007; Radua et al., 2010; Robinson, 1995; Scarone et al., 1992), the globus pallidus (Chen et al., 2022; Szeszko et al., 2004), the cerebellum (Narayanaswamy et al., 2016; Pujol et al., 2004; Shobeiri et al., 2023; Tang et al., 2016; Tao et al., 2023), and the orbitofrontal and other prefrontal cortices (Ahmari & Rauch, 2022; Kang et al., 2004; Whiteside et al., 2004). These brain areas are also crucial in a fundamental cognitive process, that is, sequence learning (Janacsek et al., 2020). Sequence learning underlies the information acquisition of serial ordering and regularities in the environment (Conway, 2020), either implicitly or explicitly. It also underlies the development of automatic behaviors, including the formation of social, motor, and cognitive skills or habits (Kaufman et al., 2010; Lieberman, 2000; Ullman, 2004). The shared neural background has raised the question of how SL works in OCD.

Multiple studies endeavored to answer this question by using different adaptations of the Serial Reaction Time task (SRT; Nissen & Bullemer, 1987)). 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. Improvement of visuomotor performance occurs through extensive practice (Pedraza et al., 2023) 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. Previous studies employing the SRT paradigm to map sequence learning in OCD failed to disentangle the three performance indicators related to different subcortical brain networks (Goldman et al., 2008; Marker et al., 2006; Rauch et al., 1997, 2007). 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

Regarding sequence-specific learning, three studies have detected intact performance in OCD with different adaptations of the SRT task (Rauch et al., 1997, 2007; Soref et al., 2018). In summary, the studies yielded conflicting results regarding sequence-specific learning in OCD: intact (Rauch et al., 1997, 2007; Soref et al., 2018), reduced (Goldman et al., 2008; Kathmann et al., 2005; Marker et al., 2006; Soref et al., 2018), or even impaired performance (Deckersbach et al., 2002; Vloet et al., 2010). 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 visuomotor performance improvement in individuals with OCD 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 (Deckersbach et al., 2002; Goldman et al., 2008;

Kathmann et al., 2005). 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. 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 sequence learning 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 (Janacsek et al., 2020), individuals with OCD exhibited primarily activation in the hippocampus, bilateral medial-temporal regions, and the orbitofrontal cortex during the task (Rauch et al., 1997, 2007) (Figure 1). These brain regions were previously implicated in explicit, declarative memory processes (Rauch et al., 1997, 2007; Squire, 1992), therefore, the engagement of explicit strategies during sequence learning in OCD has been proposed (Deckersbach et al., 2002; Kathmann et al., 2005; Rauch et al., 1997, 2007; Soref et al., 2018). These findings raise additional questions regarding the underlying mechanisms of this fundamental learning process in individuals with OCD.

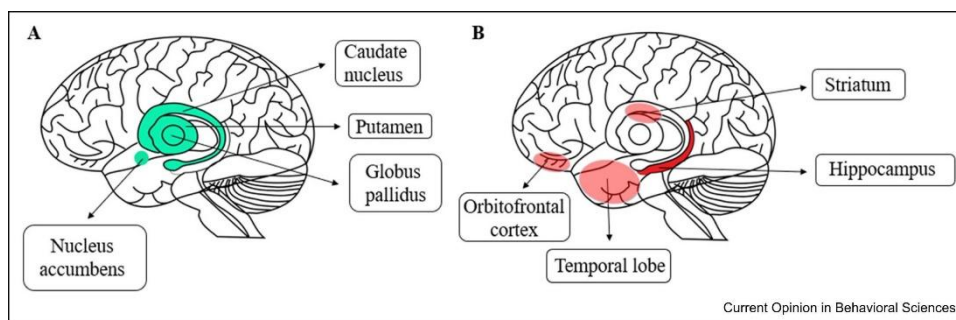


Figure 1. Schematic illustration of disparities in brain regions between (a) healthy control subjects (Janacsek et al., 2020) and (b) individuals diagnosed with OCD (Rauch et al., 1997, 2007) during the SRT task. It is important to mention that recent studies have indicated the involvement of the medial-temporal lobe and hippocampal regions in healthy individuals during SRT task (Albouy et al., 2013).

Theoretical consideration

Studies demonstrate heterogeneous results concerning the three behavioral indicators and neuroimaging data, hindering the establishment of clear conclusions and prompting further consideration. Novel approaches hold the potential to enhance our understanding of sequence learning in OCD from both neurobiological and behavioral perspectives.

The declarative memory hypothesis could provide a better explanation for this (Ullman & Pullman, 2015). It posits that as long as the declarative memory system remains relatively functional, it can effectively compensate for impaired basal ganglia-related processes, such as SL, across various disorders, including OCD (Ullman, 2004; Ullman & Pullman, 2015). In OCD, the functionality and intact nature of declarative memory processes have been confirmed (Deckersbach et al., 2002; Goldman et al., 2008; Kathmann et al., 2005; Marker et al., 2006), rendering them eligible for taking over control in implicit processes (Deckersbach et al., 2002; Goldman et al., 2008; Hart et al., 2014). 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 (Ambrus et al., 2020; Nemeth et al., 2013; Pedraza et al., 2024; Virag et al., 2015).

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 among people with OCD (Goldman et al., 2008; Leckman et al., 2007; Leopold & Backenstrass, 2015; Mataix-Cols et al., 2005; Rauch et al., 2007). Acknowledging that OCD is not a unitary condition (Bragdon et al., 2018; Leckman et al., 2007; Mataix-Cols et al., 2002, 2004, 2005), the diverse range of symptom dimensions and severities can be attributed to partially distinct neurobiological processes (Mataix-Cols et al., 2004; van den Heuvel et al., 2008).

Future directions

The primary objective of this review was to elucidate sequence 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. The 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 sequence in OCD and overcome the limitations of a classic SRT task, an alternative version, known as the Alternating Serial Reaction Time (ASRT) task (Howard & Howard, 1997), 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 (Szegedi-Hallgató et al., 2019). The complete implicitness of the task has been widely confirmed (Horváth et al., 2022; Vékony et al., 2022) as well as its high reliability (Farkas et al., 2023). Additionally, researchers should consider broadening their focus in OCD research to encompass subclinical populations.

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

Publication:

Brezóczki, B., Farkas, B. C., Hann, F., Pesthy, O., Tóth-Fáber, E., Farkas, K., Csigó, K., Németh, D., & Vékony, T. (2025). Individual differences in probabilistic learning and updating predictive representations in individuals with obsessive-compulsive tendencies. *BMC Psychiatry*, 25, 368. <https://doi.org/10.1186/s12888-025-06786-4>

Introduction

OCD is defined by the excessive and impeding presence of intrusive thoughts ('obsessions') and rigid, repetitive actions ('compulsions') (American Psychiatric Association, 2022). Compulsive actions are perceived as irrational, with individuals desiring to stop but unable to control their impulses (American Psychiatric Association, 2022; Gillan & Robbins, 2014). 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 (Banca et al., 2015; Exner et al., 2014; Gillan et al., 2011, 2014, 2015, 2016; Hansmeier et al., 2018; Joel et al., 2005; Kelmendi et al., 2016; Vaghi et al., 2019; Zetsche et al., 2015). 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 (Aslin, 2017; Conway, 2020; Horváth et al., 2022; Pedraza et al., 2024). This process is particularly significant in OCD, as it could also 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. 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 (Banca et al., 2024; Gillan et al., 2011, 2014). 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?

Methods

Two independent non-clinical samples participated in the study ($N_{\text{Study1}} = 164$, $N_{\text{Study2}} = 256$), and OC tendencies were assessed continuously using the 18-item Obsessive-Compulsive Inventory-Revised (OCI-R; Foa et al., 2002). To assess probabilistic learning, we employed a visuomotor learning paradigm, the ASRT task (Farkas et al., 2023; Howard & Howard, 1997). In Study 1, the ASRT task comprised 25 blocks, encompassing 10 repetitions of an eight-element sequence, resulting in 80 stimuli within each block. In Study 2, we utilized the same task structure but modified the task design. During the Learning phase, participants learned and practiced a predetermined probabilistic sequence (Sequence A: e.g., 2-r-4-r-3-r-1-r). 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. SL is typically quantified as the performance difference between high- and low-probability triplets. In the modified design, however, the probability of individual triplets could change between the Learning and Interference phases. Accordingly, triplets were classified based on their probability in the two phases, with the first letter referring to the Learning phase and the second to the Interference phase. Triplets that were high probability during Learning but became low probability during Interference were classified as 'H L' triplets. Conversely, triplets that were initially low probability but became high probability during Interference were classified as 'L H' triplets, whereas triplets that remained low probability across both phases were classified as 'L L' triplets. 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. (2022), 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 reflect the acquisition of the new statistical regularities introduced during the Interference phase 'New knowledge' (Horváth et al., 2022). We utilized Linear Mixed Models (LMMs) for analyzing RT, and Generalized Linear Mixed Models (GLMMs) for analyzing accuracy. These models included fixed effects for Time, Triplet Type, OC tendencies (OCI-R score), and their higher-order interactions.

Results

Probabilistic learning

In Study 1, OC tendencies did not influence either the amount or the temporal trajectory of implicit probabilistic learning as assessed by RT (Triplet Type $\times$ OCI-R score: $F_{(1, 159.45)} = 0.11$, $p = .736$; Time $\times$ Triplet Type $\times$ OCI-R score: $F_{(4, 243622.68)} = 1.66$, $p = .157$). 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 Figure 2.

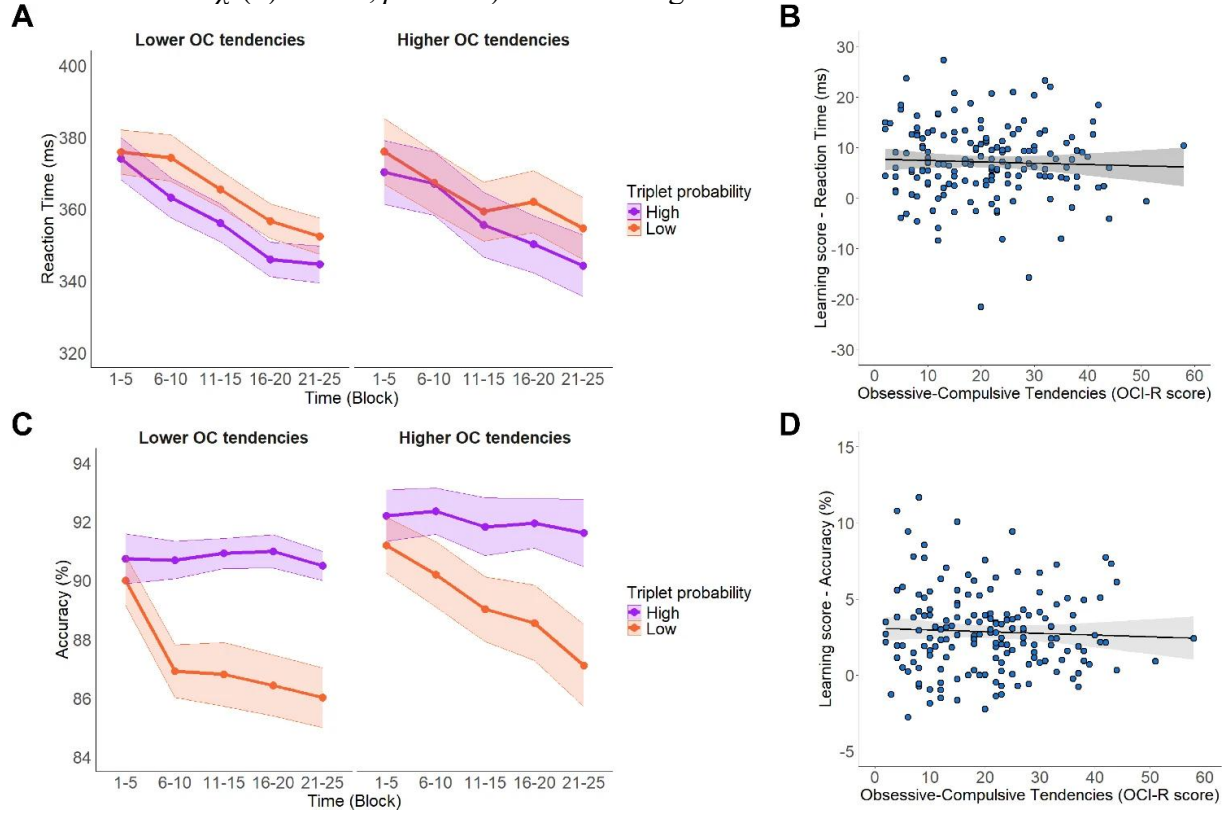


Figure 2. Probabilistic learning performance metrics as a function of OC tendencies in Study 1. **A.** Probabilistic learning performance in terms of temporal trajectory (blockwise) reaction time. The orange line represents the responses to the low-probability triplets and the purple line represents 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, y-axis indicates RT (in ms). 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. **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, y-axis indicates mean accuracy (in %). 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.

Old knowledge

OC tendencies did not modulate the resistance to previously acquired probabilistic information as assessed by RT (Triplet Type $\times$ OCI-R score: $F_{(1, 275.18)} = 0.03$, $p = .857$), nor its temporal progression (Time $\times$ Triplet Type $\times$ OCI-R score: $F_{(2, 109590.66)} = 0.63$, $p = .534$) (Figure 3A). 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 (Figure 3B).

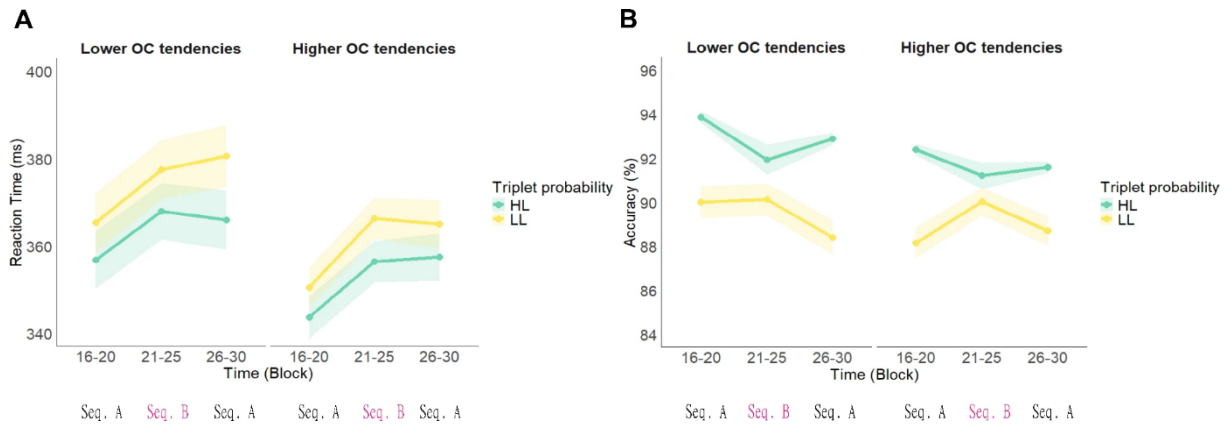


Figure 3. Participants' performance during the Interference phase of Study 2 in terms of Old knowledge. **A.** Reaction time. The green line represents the responses to 'H L' probability triplets (triplets that were high-probability during the Learning phase but became low-probability during the Interference 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, the Y-axis indicates mean reaction time (in ms). **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, the Y-axis indicates mean accuracy (in %). 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.

New knowledge

OC tendencies did not modulate the acquisition of new implicit knowledge as assessed by RT (Triplet Type $\times$ OCI-R score: $F_{(1, 276.32)} = 1.80, p = .180$), nor its temporal progression (Time $\times$ Triplet Type $\times$ OCI-R score: $F_{(2, 109860.25)} = 1.21, p = .299$) (Figure 4A). Similarly, OC tendencies did not influence the acquisition of new probabilistic information as assessed by accuracy (Triplet Type $\times$ OCI-R score: $\chi^2(1) = 1.26, p = .261$), nor its temporal progression (Time $\times$ Triplet Type $\times$ OCI-R score: $\chi^2(2) = 1.01, p = .603$) (Figure 4B).

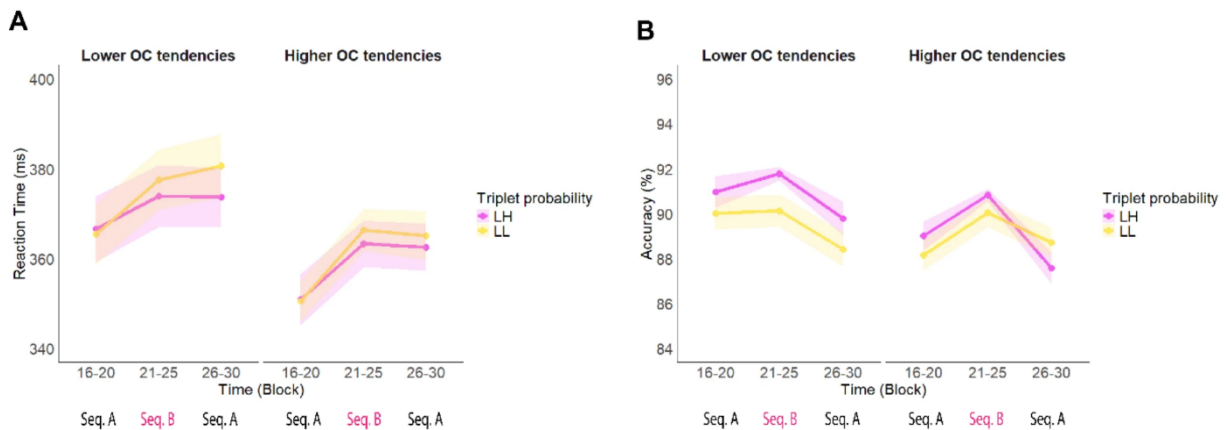


Figure 4. Participants' performance during the Interference phase of Study 2 in terms of New knowledge. **A.** Reaction time. The pink line represents the responses to the 'L H' probability triplets (that were low-probability during the Learning phase but became high-probability during the Interference 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, the Y-axis indicates mean reaction time (in ms). **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, y-axis indicates mean accuracy (in %). 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

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. Building on this, we have demonstrated that individuals with non-clinical OC tendencies can efficiently acquire second-order probabilistic contingencies. 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, as the incidental updating of predictive representations remained intact in individuals with higher OC tendencies in a non-clinical population, with no evidence of increased resistance to updating previously acquired information (Banca et al., 2024; Gillan et al., 2011). 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 (Banca et al., 2024; Gillan et al., 2011, 2014). In our study, we did not provide warnings; hence, participants were unaware they were in a learning situation and that the stimulus sequence structure changed. This allowed us to capture a much more implicit, warning-free, and non-reward driven updating mechanism. 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.

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

Publication:

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Introduction

A core challenge in human cognition involves maintaining a dynamic interplay between efficient automatic and flexible goal-directed functions to support adaptive behavior. 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) (American Psychiatric Association, 2022; Gillan et al., 2011, 2014, 2015, 2016; Yu et al., 2024). 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 (Banca et al., 2015, 2024; Gillan et al., 2011, 2014, 2015, 2016; Graybiel & Rauch, 2000; Yu et al., 2024). 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. 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. An alternative way to examine this balance at the functional level is to assess automatic and goal-directed processes across distinct neurocognitive functions, such as unsupervised learning and executive functioning. One such unsupervised learning mechanism is statistical learning (SL). 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 executive functions (Ambrus et al., 2020; Pedraza et al., 2024; Poldrack et al., 2001). The present study aimed to uncover the interplay between SL and cognitive flexibility, a key executive function, and to investigate individual differences in their interaction among university students with varying levels of OC tendencies. Based on existing literature, we hypothesized an antagonistic relationship between SL and cognitive flexibility. 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.

Methods

We recruited 404 adult participants from university courses for an online experiment. SL was assessed using the ASRT task (Farkas et al., 2023; Howard & Howard, 1997). Cognitive flexibility was operationalized as the number of perseverative errors on the Card Sorting Task (CST), a widely accepted and extensively used measure of cognitive flexibility (Fox et al., 2013). OC tendencies were assessed dimensionally using the Obsessive-Compulsive Inventory, (OCI-12; Abramovitch et al., 2021). Linear mixed-effects models were used to examine the relationship between SL, cognitive flexibility, and OC tendencies.

Results

Accuracy

No significant effects of interest emerged for RT. However, the accuracy-based analyses revealed a significant interaction between SL and cognitive flexibility: a significant Triplet Type $\times$ Perseverative Error interaction revealed an antagonistic relationship between SL and cognitive flexibility ($F_{(1, 400.52)} = 4.48, p = .035$), with greater statistical learning linked to reduced cognitive flexibility, that is higher number of perseverative errors: ($b_{\text{Low perseverative errors}} = 1.95, 95\% \text{ CI } [1.59, 2.30]$; $b_{\text{Mean perseverative errors}} = 2.22, 95\% \text{ CI } [1.97, 2.47]$; $b_{\text{High perseverative errors}} = 2.50, 95\% \text{ CI } [2.13, 2.86]$). Pairwise comparisons indicated that the statistical learning increased significantly with perseverative errors ($b_{\text{Low perseverative errors} - \text{Mean perseverative errors}} = -0.28, 95\% \text{ CI } [-0.53, -0.02], p = .034$; $b_{\text{Low perseverative errors} - \text{High perseverative errors}} = -0.55, 95\% \text{ CI } [-1.06, -0.04], p = .034$; $b_{\text{Mean perseverative errors} - \text{High perseverative errors}} = -0.28, 95\% \text{ CI } [-0.53, -0.02], p = .034$). However, a significant Triplet Type $\times$ Perseverative Error $\times$ OCI-12 score interaction indicated that OC tendencies modulate the antagonistic relationship between SL and cognitive flexibility ($F_{(1, 400.30)} = 6.21, p = .013$). 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 with statistical learning, with a significant slope ($b = 0.145, SE = 0.048, z = 2.97, 95\% \text{ CI } [0.050, 0.242], p = .002$). A similar but weaker positive relationship was observed at the medium level of OC tendencies ($b = 0.069, SE = 0.032, z = 2.11, 95\% \text{ CI } [0.005, 0.134], p = .034$), 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 ($b = -0.006, SE =$

.040, $z = -0.17$, 95% CI $[-0.086, 0.072]$, $p = .862$) (Figure 5). Overall, SL 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 SL. This antagonistic pattern weakened in participants with high OC tendencies, where SL remained moderate regardless of cognitive flexibility.

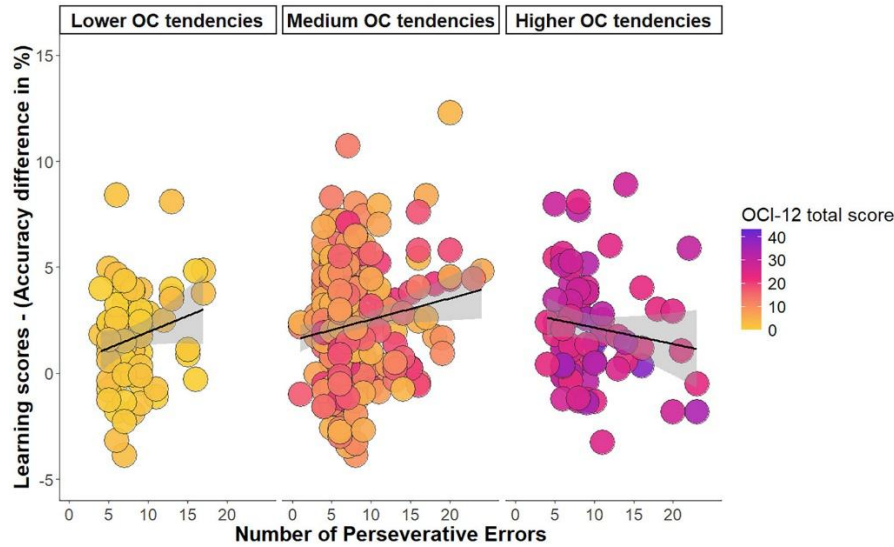


Figure 5. Relationship between cognitive flexibility and accuracy-based statistical learning across OCI-12 scores. The figure illustrates the relationship between cognitive flexibility, as measured by the number of perseverative errors on the card sorting task along the x axis, and statistical learning 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.

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 with non-clinical OC tendencies. Our findings corroborate previous theories indicating a competitive interaction between SL and executive functions, specifically cognitive flexibility (Ambrus et al., 2020; Pedraza et al., 2024; Poldrack et al., 2001). 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 (Banca et al., 2024; Gillan et al., 2011, 2015; Yu et al., 2024). Rather, it suggests a breakdown in their coordinated interaction. From this perspective, OC tendencies may be better characterized by altered coordination between cognitive systems than by dysfunction within any single function. 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.

V. General discussion

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).

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 et al., 2011, 2015; Hansmeier et al., 2018; Zetsche et al., 2015). Besides providing valuable insights, these models make it difficult to isolate pure learning processes from reward contingencies and other confounding factors. 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).

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). 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. Importantly, the present findings concern regularities that were both acquired and updated incidentally, without explicit instruction about the underlying structure or sequence-specific reinforcement. 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.

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 et al., 2024). 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, 2014, 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 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). Importantly, the present study also examined this balance through neurocognitive components 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. 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 et al., 2011, 2014, 2015; Robbins et al., 2019)

Implications

Extending this framework further highlights the importance of examining cognitive processes not in isolation but in terms of their dynamic interactions. 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 others. Furthermore, the spectrum approach offers a 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). 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 reaches clinical levels, but also across varying traits and phenomenological dimensions.

A central methodological contribution of this dissertation is the use of probability-based, implicit paradigms that enable a more precise assessment of unsupervised learning while addressing key limitations in prior OCD research. 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). 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. 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.

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