Obsessive-Compulsive Tendencies Shift the Balance Between Competitive Neurocognitive Processes

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Abstract

Theoretical models of Obsessive-Compulsive Disorder (OCD) propose that its symptoms stem from an imbalance between habitual and goal-directed processes, marked by a bias toward habitual behavior and deficits in goal-directed control. While much of the existing research has focused on reward-based learning, the contribution of reward-independent learning processes to this imbalance remains unclear. To address this gap, the present study investigated the interaction between statistical learning (SL), a form of reward-free learning, and cognitive flexibility, a key goal-directed function, in a non-clinical population. By adopting a dimensional approach to obsessive-compulsive (OC) tendencies, this work aims to overcome the limitations of categorical diagnoses and better capture the continuous, nuanced variability of symptoms, while clarifying how specific neurocognitive processes relate to OC tendencies. A total of 402 participants from the non-clinical population completed an online study involving the Alternating Serial Reaction Time (ASRT) task to assess SL and a Card Sorting Task to measure cognitive flexibility. Our findings revealed a competitive relationship between SL and cognitive flexibility. Critically, this inverse association weakened as OC tendencies increased, suggesting that even at non-clinical levels, OC tendencies may interfere with the typical interplay between automatic and goal-directed processes. Notably, SL performance remained intact, and the observed effects were not attributable to reward sensitivity, as learning occurred without external feedback. These findings emphasize the value of examining non-clinical OC tendencies and highlight the importance of investigating neurocognitive system interactions, rather than isolated functions, in advancing our understanding of OCD.

Keywords: statistical learning, cognitive flexibility, obsessive-compulsive disorder, spectrum approach, competitive memory systems

Introduction

A core challenge in human cognition involves maintaining a dynamic interplay between efficient automatic processes and flexible goal-directed processes to support adaptive behavior. Goal-directed processes involve a broad set of executive functions – including sustained attention, cognitive flexibility, inhibitory control, and working memory updating (Diamond, 2013; Friedman & Robbins, 2022; Miyake et al., 2000). In contrast, automatic processes rely on previously acquired associations and operate with reduced conscious engagement (Ashby et al., 2010; Kaufman et al., 2010; Pedraza, Farkas, et al., 2024). 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, 2015, 2016; Gillan & Robbins, 2014). 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 presence of OCD (Abramowitz et al., 2014; Brezóczki et al., 2025; Foa et al., 2002; Fullana et al., 2010; Hajcak et al., 2004; Mataix-Cols et al., 1999, 2005; Ramakrishnan et al., 2022; Zermatten et al., 2006). Considering OC tendencies from a dimensional perspective 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 (Gillan et al., 2016, 2017, 2020; Gillan & Rutledge, 2021). Therefore, the present study aimed to delineate the role of the balance between automatic and goal-directed processes underlying maladaptive symptoms of OCD by assessing OC tendencies as a dimensional spectrum within the non-clinical population.

Prominent theoretical models propose that the repetitive and recurrent symptoms of OCD arise from maladaptive habitual processes driven by impairments in goal-directed processes (Gillan et al., 2011, 2015, 2016; Graybiel & Rauch, 2000). These theoretical models are grounded in supervised, reward-based paradigms, suggesting that extensively trained stimulus–response associations can become so rigid and automatic that they override goal-directed control, even when the outcome has been (Gillan, 2021; Gillan et al., 2011; Gillan & Robbins, 2014). As a result, behavior becomes excessively habitual and automatic. However, this framework leaves an important question open. While a bias toward habitual responding characterizes OCD, it is also associated with aberrant reward processing (Alves-Pinto et al., 2019; Figee et al., 2011; Kaufmann et al., 2013; Koch et al., 2018). This raises the question of whether learning in OCD is primarily driven by reward or whether the enhanced habitual behavior reflects underlying alterations in pure learning mechanisms independent of reward sensitivity. 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 (Zhong et al., 2025). From this perspective, supervised learning emerges as a secondary process built upon earlier, reward-free, unsupervised mechanisms. Accordingly, to better understand the development and persistence of automatic, compulsive behavioral characteristics of OCD and OC tendencies, it is essential to disentangle reward sensitivity and pure learning mechanisms (Brezóczki et al., 2025) and to

revisit the primary role of unsupervised learning and its interaction with goal-directed processes.

One such unsupervised learning mechanism is statistical learning (SL), a fundamental process that supports the acquisition of skills and habits through the incidental extraction of novel probabilistic patterns from the environmental stream (Aslin, 2017; Conway, 2020; Horváth et al., 2022; Pedraza, Farkas, et al., 2024; Theeuwes et al., 2022). SL in clinical OCD populations has shown both impairments and intact results (for review see: Brezóczki et al., 2023), while non-clinical individuals with OC tendencies demonstrate intact or even faster learning rates (Brezóczki et al., 2025). This highlights the need to better understand how other neurocognitive processes 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 processes (Ambrus et al., 2020; Horváth et al., 2022; Nemeth et al., 2013; Pedraza, Farkas, et al., 2024; Pedraza, Vékony, et al., 2024; Poldrack et al., 2001; Tóth-Fáber et al., 2021; Virag et al., 2015). Typically, increased reliance on one system corresponds with reduced engagement of the other, as demonstrated by the inverse relationship between SL and goal-directed processes. If OCD and OC tendencies involve a disruption in the balance between automatic and goal-directed processes, then investigating their interaction outside the influence of supervision becomes particularly informative.

To provide a complementary perspective on the neurocognitive mechanisms underlying OCD, this study focused on SL and goal-directed processes, specifically cognitive flexibility. SL was assessed using an unsupervised learning paradigm, the Alternating Serial Reaction Time (ASRT) task (Farkas et al., 2023; Howard & Howard, 1997), which lacks the reward and reinforcement-based factors typically found in supervised learning tasks. Cognitive flexibility was measured using the Card Sorting Task (Fox et al., 2013). The present study aimed to uncover the interplay between SL and cognitive flexibility and to investigate how non-clinical OC tendencies may modulate this relationship. 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 Card Sorting Task. 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

Participants

A total of 568 university students took part in the study through an online experiment in exchange for course credit. To maintain data integrity, rigorous quality control procedures were implemented, resulting in the exclusion of 166 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 402 participants (283 female, 111 male, and 3 non-specified; $M_{Age} = 22.08$ *years;* $SD_{Age} = 5.11$). 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.

Measures

Alternating Serial Reaction Time task

Statistical learning was measured by the Alternating Serial Reaction Time (ASRT) task (Farkas et al., 2023; Howard & Howard, 1997). The task was implemented in JavaScript using jsPsych version 6.1.0 (Vékony, 2021). 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. Still, no information was provided about their learning performance, as they were unaware that the task involved detecting a hidden regularity.

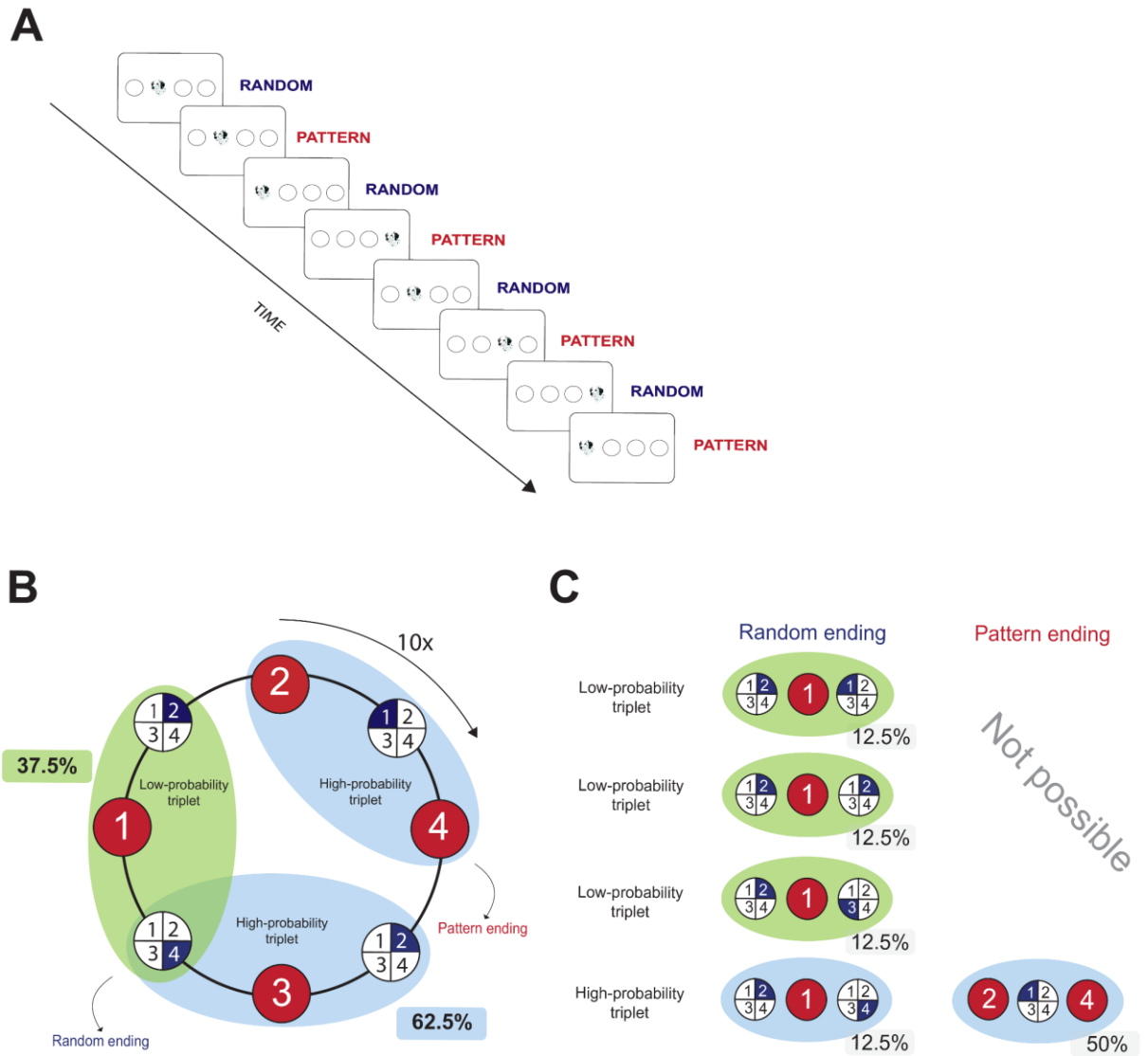

Figure 1. Structure of the ASRT task. (A) In the Alternating Serial Reaction Time (ASRT) task, participants were instructed to respond by pressing keys corresponding to the spatial location of a target stimulus, depicted as a dog's head. Each trial followed an eight-element probabilistic sequence composed 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 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.

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 (de Leeuw, 2015; Fox et al., 2013; Vékony, 2022). 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. 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. The task comprises a total of sixty-four trials. The underlying categorization rule changes after every sequence of ten consecutive correct 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-Revised

Obsessive-compulsive tendencies were assessed using the revised version of the Obsessive-Compulsive Inventory (OCI-R; Foa et al., 2002), an 18-item 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. The OCI-R has demonstrated strong psychometric validity, including high internal consistency and test-retest reliability, in both clinical (Foa et al., 2002; Huppert et al., 2007) and non-clinical samples (Hajcak et al., 2004; Zermatten et al., 2006). The total score can vary from 0 to 72. In our final sample, the observed scores ranged from 0 to 58 (M = 16.61; SD = 11.90); see Figure 2.

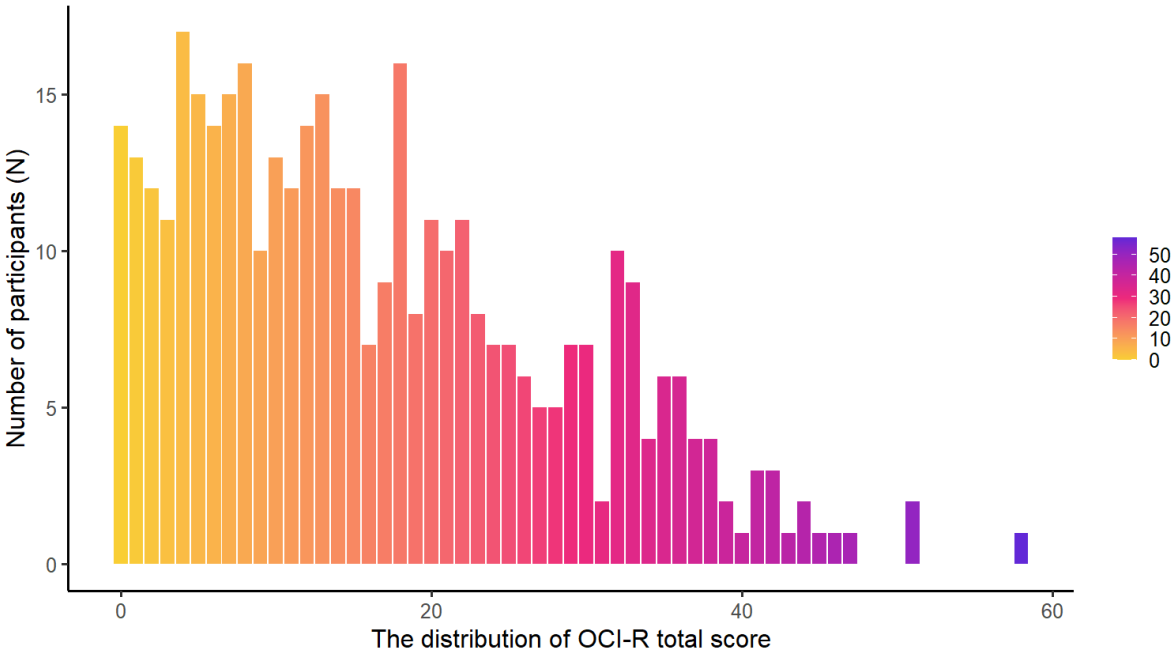

Figure 2. The distribution of the participants' OC tendencies as measured by the OCI-R total score in the sample. The x-axis indicates the total OCI-R score, while the y-axis indicates the number of participants. The color gradient transitions from yellow, through pink, to purple, reflecting increasing levels of OC tendencies.

Procedure

The experiment was conducted using the Gorilla Experiment Builder platform (https://www.gorilla.sc) (Anwyl-Irvine et al., 2020). 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 (Horváth et al., 2022; Vékony et al., 2022). Following the ASRT task, cognitive flexibility was evaluated using the CST, and obsessive-compulsive tendencies were measured with the OCI-R. Additionally, 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

To ensure data validity, we implemented data quality control measures in accordance with established guidelines for online experiments (Rodd, 2024). 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, 4.40%); 4) had unusually low performance on the ASRT task (accuracy below 80%) (N = 23, 4.05%); 5) age exceeding 55 years (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 hours, recreational drugs or psychoactive medications within 24 hours before the experiment (N = 38, 6.69%); 8) had a long delay between the ASRT blocks (N = 4, 0.7%), 9) random buttom pressing during ASRT task (N = 6, 1.06%) 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 166 participants (29.23%).

Data preparation and analysis

Data preprocessing, statistical analysis, and visualization were carried out in R version 4.3.3 (R Core Team, 2022). 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 (Brezóczki et al., 2025). 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 (Horváth et al., 2022; Soetens et al., 2004). 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, 17.96% of trials were excluded from accuracy analyses and 25.05% from RT analyses. These exclusion rates are consistent with those reported in online ASRT studies (Brezóczki et al., 2025; Hann et al., 2024; Nagy et al., 2025; Vékony, Brezóczki, et al., 2025; Vékony, Farkas, et al., 2025)

We utilized Linear Mixed Models (LMMs) for analyzing RT and accuracy performance. LMMs were fit with the mixed function from the afex package (Singmann et al., 2024). 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-R score), and their higher-order interactions as fixed effects in the model. The Time, OCI-R 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 Block. For accuracy, the final model achieved convergence using the participants as random intercepts with by-participant correlated slopes for Triplet Type and Time.

Post hoc analyses involved the computation of estimated marginal means and marginal trends for simple effects and simple slopes, utilizing the emmeans package (Lenth, 2018).

Significant interactions involving continuous predictors, specifically the OCI-R 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 the ggplot2.

In reporting the results, the main effects of Time are 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 statistical learning throughout the task. 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), medium OC tendencies (Mean OCI-R score) and higher OC tendencies (Mean OCI-R score + SD), based on standard deviations from the mean.

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

Reaction time:
*MedianRT ~ Time * Triplet Type * OCI-R score * Perseverative error + (Time | Participant)*

Accuracy:
*MeanAccuracy ~ Time * Triplet Type * OCI-R score * Perseverative error + (Time + Triplet Type | Participant)*

Results

How do OC tendencies modulate the interplay between cognitive flexibility and statistical learning? - Reaction Time

Regarding RT, the model reported a main effect of Triplet Type, indicating faster RTs for high-probability trials compared to low-probability trials ($F_{(1, 11244.92)} = 195.06$, $p < .001$), which evidences statistical learning during the task ($b = -2.98$, $SE = .213$). The main effect of Time indicated a decrease in RTs throughout the task ($F_{(1, 397.80)} = 160.74$, $p < .001$), demonstrating changes in visuomotor performance over time ($b = -1.21$, $SE = 0.957$). Statistical learning improved gradually during the task, as reflected by the interaction between Triplet Type and Time ($F_{(1, 11244.98)} = 8.98$, $p = .003$) due to a difference between high- and low-probability trials as the task progressed ($b_{\text{Block 5}} = -5.08$, $SE_{\text{Block 5}} = .520$; $b_{\text{Block 10}} = -6.56$, $SE_{\text{Block 10}} = .471$; $b_{\text{Block 15}} = -8.04$, $SE_{\text{Block 15}} = .814$). There was a statistically significant main effect of Perseverative error ($F_{(1,398.00)} = 7.68$, $p = .006$), indicating that weaker cognitive flexibility (more perseverative errors) was associated with significantly slower reaction times ($b = 1.31$, $SE = 0.474$), as well as with better visoumotor performance (Time * Perseverative error: $F_{(1,397.77)} = 3.95$, $p = .048$; $b = -0.05$, $SE = 0.024$). The absence of a statistically significant interaction, including Perseverative errors, suggests no indication of an antagonistic relationship between statistical learning and cognitive flexibility (Triplet Type * Perseverative

error: $F_{(1,11244.90)} = 0.07$, $p = .792$, Triplet Type * Time * Perseverative error: $F_{(1,11244.93)} = 1.12$, $p = .290$). Furthermore, the main effect of OCI-R score was statistically significant ($F_{(1, 398.00)} = 7.49$, $p = .006$), indicating faster reaction times with higher levels of OC tendencies *(b = -0.43, SE = 0.157)*, yet no influence on statistical learning (Triplet Type * OCI-R score: $F_{(1,11244.95)} = 0.00$, $p = .993$, Triplet Type * Time * OCI-R score: $F_{(1,11245.04)} = 0.25$, $p = .529$), visuomotor performance (Time * OCI-R score: $F_{(1,397.82)} = 1.12$, $p = .291$), cognitive flexibility (OCI-R score * Perseverative error: $F_{(1, 398.00)} = 0.10$, $p = .749$), and nor the interplay between statistical learning and cognitive flexibility (Triplet Type * Perseverative error * OCI-R score: $F_{(1,11244.93)} = 1.61$, $p = .204$ (Figure 3), Time * Perseverative error * OCI-R score: $F_{(1,397.80)} = 2.31$, $p = .129$, Triplet Type * Time * Perseverative error * OCI-R score: $F_{(1,11244.99)} = 1.18$, $p = .277$, see full results in Supplementary Table S1.1.).

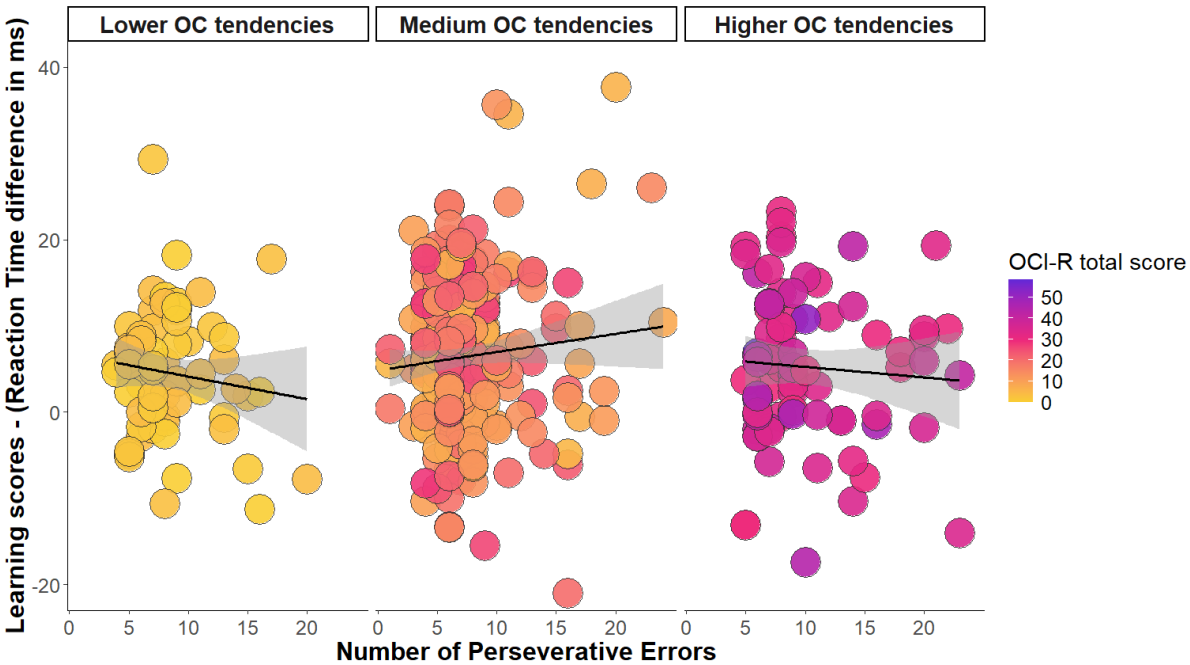

Figure 3. The figure illustrates the relationship between cognitive flexibility, as measured by the number of perseverative errors on the CST along the x-axis, and statistical learning performance along the y-axis, which is operationalized as the difference in reaction time between high- and low-probability triplets. Each point represents an individual participant, with color encoding their total OCI-R score along a continuous gradient from low (yellow) through intermediate (pink) to high (purple) obsessive-compulsive symptom severity. A linear regression line with 95% confidence intervals is overlaid in black. While the OCI-R 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-R 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 the level of OC tendencies.

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

High-probability trials yielded higher accuracy than low-probability trials ($F_{(1, 398.02)} = 291.43$, $p < .001$), evidencing statistical learning ($b = 1.10$, $SE = .064$). Accuracy decreased throughout the task (Time: $F_{(1, 398.08)} = 57.63$, $p < .001$; $b = -0.14$, $SE = .019$), and statistical learning improved as the task progressed (Time * Triplet Type: $F_{(1, 10847.59)} = 32.75$, $p < .001$; ($b_{\text{Block 5}} = 1.74$, $SE_{\text{Block 5}} = .153$; $b_{\text{Block 10}} = 2.52$, $SE_{\text{Block 10}} = 0.140$; $b_{\text{Block 15}} = 3.30$; $SE_{\text{Block 15}} = .232$). There was a statistically significant main effect of Perseverative error ($F_{(1,397.99)} = 6.00$, $p = .015$), suggesting that higher perseverative error rates may predict lower response accuracy ($b = -0.11$, $SE = .045$), accompanied by a deterioration in visuomotor performance as the task progressed (Time * Perseverative error interaction $F_{(1,398.04)} = 4.22$, $p = .041$, with more flexibility in Block 5: $b_{Block\ 5} = 91.57$, $SE_{Block\ 5} = .262$; reduced flexibility in Block 15: $b_{Block\ 15} = 89.13$, $SE_{Block\ 15} = .310$). A statistically significant Triplet Type * Perseverative error interaction ($F_{(1,398.00)} = 4.48$, $p = .035$) demonstrated an antagonistic relationship between statistical learning and cognitive flexibility, with greater statistical learning linked to reduced cognitive flexibility (higher number of perseverative errors). ($b_{Low\ Perseverative\ errors} = 1.93$, $SE_{Low\ Perseverative\ errors} = .182$; $b_{Mean\ Perseverative\ errors} = 2.21$, $SE_{Mean\ Perseverative\ errors} = .129$; $b_{High\ Perseverative\ errors} = 2.49$, $SE_{High\ Perseverative\ errors} = .187$), except when considering the trajectory of learning (Triplet Type * Time * Perseverative error: $F_{(1,10847.44)} = 0.06$, $p = .814$). OC tendencies do not influence overall accuracy ($F_{(1, 398.00)} = 0.35$, $p = .553$), visuomotor performance (Time * OCI-R score: $F_{(1, 398.12)} = 0.27$, $p = .606$), nor statistical learning (Triplet Type * OCI-R score: $F_{(1, 398.08)} = 0.30$, $p = .586$) and its improvement with time (Triplet Type * Time * OCI-R score: $F_{(1, 10847.71)} = 0.46$, $p = .496$). Similar to RT, we found no interaction between OC tendencies and perseverative errors on overall accuracy ($F_{(1, 398.00)} = 0.53$, $p = .466$), as well as on visuomotor performance (Time * Perseverative errors * OCI-R score: $F_{(1, 398.08)} = 0.57$, $p = .451$). However, a statistically significant interaction between Triplet Type * Perseverative error * OCI-R score ($F_{(1, 398.10)} = 4.84$, $p = .028$) 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. For lower OC tendencies, statistical learning (High – Low difference) was smallest at a low number of perseverative errors ($b_{Low\ Perseverative\ errors} = 1.59$, $SE_{Low\ Perseverative\ errors} = 0.26$), increased at mean perseverative errors ($b_{Mean\ Perseverative\ errors} = 2.14$, $Se_{Mean\ Perseverative\ errors} = 0.18$), and was largest at high perseverative errors ($b_{High\ Perseverative\ errors} = 2.68$, $SE_{High\ Perseverative\ errors} = 0.27$). For medium OC tendencies, the corresponding differences were ($b_{Low\ Perseverative\ errors} = 1.93$, $SE_{Low\ Perseverative\ errors} = 0.18$; $b_{Mean\ Perseverative\ errors} = 2.21$, $SE_{Mean\ Perseverative\ errors} = 0.13$; $b_{High\ Perseverative\ errors} = 2.49$, $SE_{High\ Perseverative\ errors} = 0.19$). However, this relationship weakens in individuals with high OC tendencies: $b_{Low\ Perseverative\ errors} = 2.27$, $SE_{Low\ Perseverative\ errors} = 0.27$; $b_{Mean\ Perseverative\ errors} = 2.28$, $SE_{Mean\ Perseverative\ errors} = 0.19$; and a higher number of perseverative errors: $b_{High\ Perseverative\ errors} = 2.29$, $SE_{High\ Perseverative\ errors} = 0.22$). With high 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. However, this effect was not present in the trajectory of learning: Triplet Type * Time * Perseverative errors * OCI-R score: $F_{(1, 10847.57)} = 1.51$, $p = .219$, see full results in Supplementary Table S1.2.).

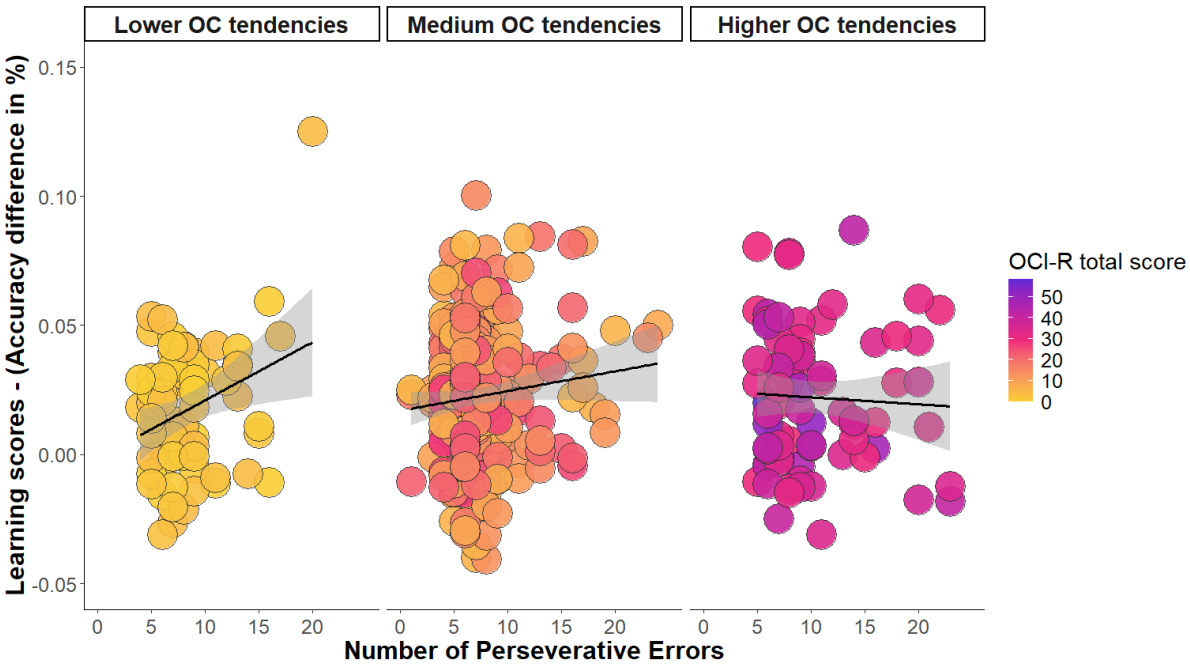

Figure 4. The figure illustrates the relationship between cognitive flexibility, as measured by the number of perseverative errors on the CST along the x-axis, and statistical learning performance along the y-axis, which is operationalized as the difference in accuracy between high- and low-probability triplets. Each point represents an individual participant, with color encoding their total OCI-R score along a continuous gradient from low (yellow) through intermediate (pink) to high (purple) obsessive-compulsive symptom severity. A linear regression line with 95% confidence intervals is overlaid in black. While the OCI-R 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-R 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 processes in the context of OC tendencies.

Discussion

In this study, we addressed a critical gap in our understanding of cognitive control by examining the interplay between unsupervised statistical learning (SL) and goal-directed cognitive flexibility. We specifically investigated how this relationship is modulated by obsessive-compulsive (OC) tendencies within a non-clinical population. We aimed to elucidate the interplay between statistical learning and cognitive flexibility and to assess how non-clinical OC tendencies modulate this relationship. We conducted online experiments on a non-clinical population, measuring OC tendencies along a continuous spectrum from mild to elevated levels. SL was evaluated using an unsupervised learning task while cognitive flexibility was assessed. Our findings corroborate previous theories indicating a competitive

interaction between SL and cognitive flexibility; however, they also reveal that this inverse relationship diminishes as OC tendencies increase.

Our results addressed a gap by elucidating the interaction between unsupervised learning, a primary form of learning (Zhong et al., 2025), and goal-directed processes among OC tendencies. Consistent with prior findings, unsupervised learning, namely SL, was found to be preserved (Brezóczki et al., 2025), suggesting this core learning mechanism remains intact across OC tendencies. This preservation is particularly noteworthy, as the excessive bias toward habitual behaviour in OCD may stem, in part, from reward-driven learning. In feedback- or reward-based contexts, 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 automatic processes and reducing the opportunity for flexible behavioral adaptation. However, in the present study, where learning occurred in the absence of external feedback, our findings indicate that the interaction between SL and cognitive flexibility is not influenced by heightened reward sensitivity. Although the pure learning processes remained intact, the interaction of SL with goal-directed processes 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 OCD (Gillan et al., 2011, 2014; Gruner et al., 2016; Robbins et al., 2019). Accordingly, future research comparing supervised and unsupervised learning processes and their interaction with goal-directed processes across the OC spectrum is essential to better understand the neurocognitive basis of maladaptive behaviors in OCD.

Furthermore, our results build upon existing theories that highlight a disruption between automatic and goal-directed processes in both clinical OCD and subclinical OC tendencies (Gillan, 2021; Gillan et al., 2011, 2014, 2016; Gillan & Robbins, 2014; Graybiel & Rauch, 2000; Ramakrishnan et al., 2022; Robbins et al., 2019). Specifically, we show that OC tendencies modulate the competitive interaction between these processes, particularly between SL and cognitive flexibility. Those theories typically propose that a shift toward habitual, automatic behavior arises from impaired goal-directed control, wherein increased automaticity is coupled with reduced goal-directed functioning in individuals with OCD and elevated compulsive traits (Gillan et al., 2011, 2014; Gillan & Robbins, 2014; Robbins et al., 2019, 2024; Vaghi et al., 2019). Our results extend these findings, demonstrating that the inverse relationship typically observed in non-clinical populations (Ambrus et al., 2020; Pedraza, Farkas, et al., 2024; Pedraza, Vékony, et al., 2024), namely, that better SL is associated with weaker goal-directed performance, is weakened among individuals with higher OC tendencies. This suggests that even below the clinical threshold, OC traits may disrupt the adaptive balance between automatic and goal-directed behavior (Gillan et al., 2017, 2020; Ramakrishnan et al., 2022). This finding suggests that for individuals with higher OC tendencies, performance in statistical learning becomes decoupled from their cognitive flexibility, indicating that the typical trade-off between these two processes is disrupted.

The discrepancy between our findings and previous results may be explained by differences in methodological approaches. Earlier studies predominantly employed outcome devaluation and contingency degradation paradigms, which typically assess learning after extended instrumental training and evaluate goal-directed behavior based on participants' ability to adapt to changed rules and feedback in one experimental design (Gillan et al., 2011,

2014, 2016). At the same time, our findings align with the perspective that neither habitual, automatic processes nor cognitive inflexibility alone serve as robust predictors of OC symptomatology; rather, it is the interaction between these factors, specifically, reduced flexibility combined with heightened automaticity, that better accounts for symptom presence (Ramakrishnan et al., 2022). But unlike this previous study that measured generative cognitive flexibility and assessed habitual tendencies via self-report questionnaires (Ramakrishnan et al., 2022), our study specifically examined reactive cognitive flexibility, which a recent meta-analysis has challenged as being independently impaired in OCD (Fradkin et al., 2018).This may explain why, unlike previous findings showing an inverse relationship, we observe a weakened rather than inverse association between these processes at higher levels of OC tendencies. To advance understanding of OC tendencies and the pathophysiology of OCD, future studies should endeavor to replicate these findings using dual-task paradigms that concurrently integrate learning mechanisms and cognitive flexibility within a dual-task design.

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 symptomatology. Our results imply that the weakened interplay observed among higher OC tendencies could serve as a potential predictor of OC symptomatology (Gillan, 2021; Gillan et al., 2011, 2014, 2016; Ramakrishnan et al., 2022) Alongside theoretical frameworks that propose a bias toward automatic processes in clinical OCD (Gillan, 2021; Gillan et al., 2011, 2014; Gillan & Robbins, 2014; Graybiel & Rauch, 2000; Ramakrishnan et al., 2022; Robbins et al., 2019; Vaghi et al., 2019) other perspectives emphasize the potential emergence of compensatory mechanisms, wherein impairments in implicit processing are offset by increased engagement of controlled, explicit processes to maintain effective performance (Brezóczki et al., 2023; Deckersbach et al., 2002; Soref et al., 2018, 2021; Ullman, 2004; Ullman & Pullman, 2015). 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 a more cooperative or compensatory way of interaction. Our findings align with this perspective, as they suggest that the characteristics of both clinical OCD and subclinical OC tendencies may stem from atypical interactions between neurocognitive systems (Deckersbach et al., 2002; Gillan et al., 2011; Soref et al., 2018, 2021; Ullman, 2004; Ullman & Pullman, 2015) 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, as hypothesized, compensatory mechanisms reshape the dynamic toward a more cooperative and functionally adaptive interaction in clinical OCD.

It is important to note that our study was conducted on a non-clinical population of healthy young adults. Importantly, previous research has demonstrated that OC tendencies can influence a broad range of neurocognitive functions, including statistical learning (Brezóczki et al., 2025), inhibitory control (Dominke et al., 2021), cognitive flexibility (Ramakrishnan et al., 2022), and decision-making (Hauser et al., 2017; Hoven et al., 2024; Scholl et al., 2022; Vaghi et al., 2017). This can prove that this approach serves as an effective methodological tool for identifying individual differences in neurocognitive processes. 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 processes is maintained at lower levels of OC tendencies, this interaction potentially be absent in the clinical populations, resulting in impaired adaptive behavior. This disruption could be anticipated by higher subclinical OC tendencies. It is also possible that this inverse relationship between these processes persists at the clinical level but manifests in an exaggerated, potentially nonlinear manner, consistent with a U-shaped function across the OC spectrum. To clarify these dynamics, it is essential to extend investigations to the clinical population in future research.

Some limitations should be noted in the present study. First, the relatively high exclusion rate, a common challenge in online experimental designs (Brezóczki et al., 2025; Hann et al., 2024; Nagy et al., 2025; Rodd, 2024; Vékony, Brezóczki, et al., 2025; Vékony, Farkas, et al., 2025) 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. Additionally, we did not control for other disorders that are often associated with elevated compulsivity and frequently comorbid with OCD (Choi et al., 2020; Gillan et al., 2016; Goodwin, 2015). Second, presenting the tasks in a fixed order may have introduced potential order or fatigue effects. Tasks presented later in the session may have been influenced by declining attention or cognitive fatigue. Future research could address this limitation by counterbalancing task order to minimize such effects.

To conclude, our results support the competitive memory systems hypothesis (Ambrus et al., 2020; Horváth et al., 2022; Pedraza, Farkas, et al., 2024; Pedraza, Vékony, et al., 2024; Poldrack et al., 2001) by elucidating a 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.

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Contributions

B. B.: Conceptualization, Software, Validation, Investigation, Data Curation, Formal analysis, Writing – Original Draft, Writing – Review & Editing, Visualization; T.V.: Conceptualization, Software, Validation, Investigation, Data Curation, Formal analysis, Resources, Writing – Review & Editing, Supervision; B. C. F.: Methodology, Validation, Writing – Review & Editing, F. H.: Writing – Review & Editing; D.N.: Conceptualization, Software, Validation, Resources, Writing – Review & Editing, Supervision, Funding.

Declaration of interests

The authors declare no competing interests.

Data availability statement

Data and codes for analysis are available on the following link:
https://osf.io/fwb38/?view_only=03b2754e647742a2a8e5158a39174b45

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