Obsessive-Compulsive Tendencies Shift the Balance Between Competitive Neurocognitive Functions

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Highlights

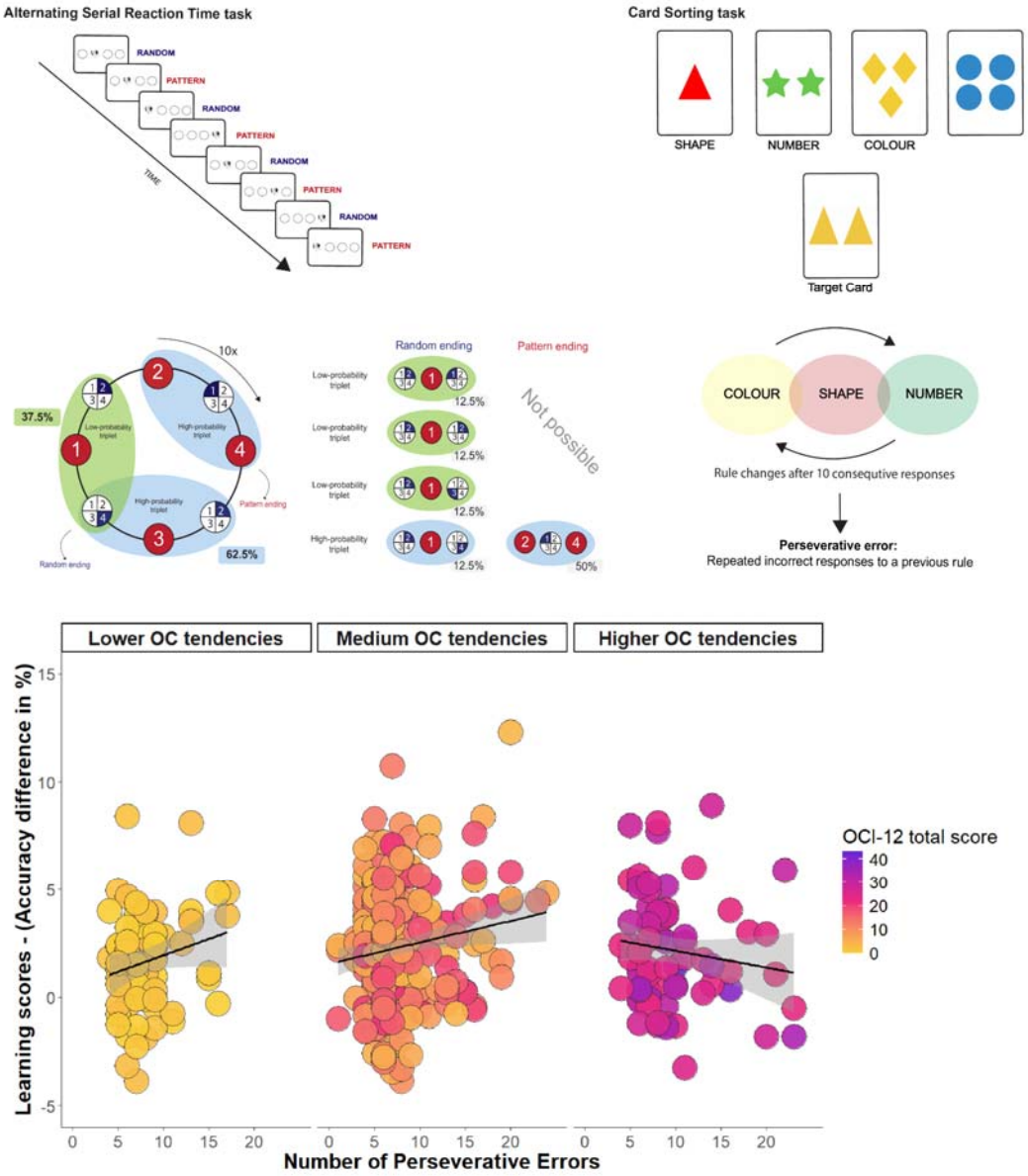
- OCD theories propose an imbalance between automatic and goal-directed control systems.
- We tested whether this imbalance emerges at a functional level, beyond reward-based learning.
- Statistical learning and cognitive flexibility showed an antagonistic relationship in a non-clinical sample.
- This inverse association weakened as obsessive–compulsive tendencies increased.
- OC tendencies alter the interaction between automatic learning and executive control even at subclinical levels.

Summary

Theoretical models of Obsessive–Compulsive Disorder (OCD) emphasize that symptoms may arise from an imbalance between habitual and goal-directed processes, characterized by increased reliance on habitual behavior and reduced efficiency of goal-directed control. However, it remains unclear whether similar alterations appear at a more general functional level, beyond reward-driven mechanisms. The present study, therefore, investigated the relationship between statistical learning (SL), an implicit, reward-independent mechanism that supports the detection of environmental regularities, and cognitive flexibility, defined as the capacity to adapt behavior and cognitive strategies to changing environmental demands. By adopting a dimensional approach to obsessive-compulsive (OC) tendencies in a non-clinical sample, we aimed to clarify how continuous symptom variability relates to the interaction of these neurocognitive processes. A total of 404 participants completed an online probabilistic sequence learning task assessing SL and a card-sorting task measuring cognitive flexibility. Results revealed an antagonistic relationship between SL and cognitive flexibility. Importantly, this inverse association weakened as OC tendencies increased, suggesting that OC tendencies may alter the typical balance between automatic and goal-directed functions even at undiagnosed levels.

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

Graphical Abstract



Introduction

A core challenge in human cognition involves maintaining a dynamic interplay between efficient automatic and flexible goal-directed functions to support adaptive behavior. Goal-directed behaviour relies on a broad set of executive functions – including sustained attention, cognitive flexibility, inhibitory control, and working memory updating [1–3]. In contrast, automatic behaviour depends on previously acquired associations and operates with reduced conscious engagement [4–6]. Disruption of this interplay can lead to behavioral difficulties, as seen in conditions such as Obsessive-Compulsive Disorder (OCD), where automaticity tends to dominate over goal-directed control, resulting in rigid, repetitive mental (obsessions) and behavioral rituals (compulsions)[7–12,58,59.] Indeed, varying degrees of obsessions and compulsive acts, collectively referred to as obsessive-compulsive (OC) tendencies, are distributed along a continuum in the general population and, when persistent and sufficiently severe, culminate in a clinical presentation of OCD [13–21]. 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 [11,13,22,23,27].Therefore, the present study aimed to delineate the role of the balance between automatic and goal-directed functions 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 symptoms of OCD and transdiagnostic tendencies arise from diminished goal-directed control coupled with a corresponding dominance of habitual responding [8,9,12,25,26,28,32,58.] Crucially, much of the empirical support for this perspective derives from dual-task paradigms that impose substantial cognitive demands by requiring the simultaneous coordination of multiple processes under state-dependent conditions, thereby illustrating how goal-directed and habitual systems interact under high cognitive load [8,9,28,29]. Within such contexts, disruptions in the balance between controlled and habitual processing may emerge, reflecting context-dependent processing constraints rather than indicating a generalized alteration in cognitive functioning. However, these state-level findings leave open the question of whether compulsive tendencies also reflect a more stable, trait-like bias in the interaction between controlled and automatized learning mechanisms. Individuals with generally weaker cognitive control may rely more consistently on simplified or habitual processing strategies not only under high task demands but also as part of a broader compensatory organization of cognitive functioning across contexts. The present study therefore aims to examine whether individual differences are systematically associated with performance across tasks that differentially engage controlled and automatized processing, with the goal of identifying stable, trait-related neurocognitive patterns underlying OC tendencies.

From a habitual perspective, a key limitation of current frameworks becomes apparent. Evidence from outcome devaluation and related feedback-based paradigms consistently points to enhanced habitual responding in OCD and compulsivity[10,12,26]. Yet in these tasks, the balance between goal-directed and habitual control is tightly coupled to continuous external reward or feedback, making it difficult to isolate learning mechanisms

from reward-driven performance. Consequently, understanding OC requires moving beyond reward-dependent paradigms to probe the underlying, feedback-independent mechanisms [20]. Addressing this question requires considering recent advances in learning theory, which emphasize the crucial role of unsupervised processes in driving neural plasticity and establishing the foundation for supervised learning [30.] From this perspective, supervised learning emerges as a later process built upon earlier, reward-free, unsupervised mechanisms [30]. Accordingly, to better understand the development and persistence of automatic, compulsive behavioral characteristics of OCD and OC tendencies, it is essential to disentangle feedback sensitivity and pure learning mechanisms [20] and to revisit the primary role of unsupervised learning and its interaction with goal-directed functions.

One such unsupervised learning mechanism is statistical learning (SL), a fundamental function that supports the acquisition of skills and habits through the incidental extraction of novel probabilistic patterns from the environmental stream [6,31,33–35]. SL in clinical OCD populations has shown both impairments and intact results (for review see: Brezóczki et al. [36]), while non-clinical individuals with OC tendencies demonstrate intact or even faster learning rates [20]. This highlights the need to better understand how other neurocognitive functions contribute to such performance. Indeed, within the framework of interactive memory systems, neurocognitive functions such as SL rarely operate in isolation; instead, they engage in dynamic and often competitive interactions with goal-directed functions [6,34,37–42] Typically, increased reliance on one system corresponds with reduced engagement of the other, as demonstrated by the inverse relationship between SL and goal-directed functions. In this context, cognitive flexibility, defined as the capacity to shift behavior, strategies, or mental frameworks in response to changing environmental demands, is a particularly critical goal-directed function [1–3], as maladaptive, rigid, and repetitive behavioral patterns of OC may reflect its impairments [43,44]. 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 profile underlying OCD and OC tendencies, this study focused on SL and goal-directed functions, specifically cognitive flexibility. Therefore, in the present study, we recruited 404 adult participants from university courses via an online experiment. SL was assessed using an unsupervised learning paradigm, the Alternating Serial Reaction Time (ASRT) task [45,46], which is a probabilistic learning task that lacks the supervision- and reinforcement-based factors on SL performance [47]. Cognitive flexibility was operationalized as the number of perseverative errors on the Card Sorting Task [48], a widely accepted and extensively used measure of cognitive flexibility [49–55]. The prevalence of undiagnosed OC tendencies was evaluated using the OCI-12 questionnaire[49.] 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.

Results

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

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

The model reported a statistically significant main effect of Triplet Type, indicating faster RTs for high-probability trials compared to low-probability trials, which evidences statistical learning during the task. The main effect of Time indicated a decrease in RTs throughout the task, demonstrating changes in visuomotor performance over time. Importantly, the interaction between Triplet Type and Time suggested that statistical learning developed gradually, as the difference between high- and low-probability trials increased over time.

Cognitive flexibility was significantly associated with overall RT performance, as reflected by a main effect of Perseverative errors, whereby a higher number of perseverative errors, indicative of reduced cognitive flexibility, predicted slower responses. However, the absence of significant interactions involving Perseverative errors suggests that cognitive flexibility did not modulate visuomotor performance (Time × Perseverative error), or statistical learning (Triplet Type × Perseverative error), nor the trajectory of statistical learning (Time × Triplet Type × Perseverative error).

In contrast, OCI-12 scores showed no significant main effect and did not interact with any of the task-related variables, indicating that OC tendencies were not associated with baseline RT (main effect of OCI-12 score), cognitive flexibility (OCI-12 score × Perseverative error), visuomotor performance (Time × OCI-12 score), statistical learning (Triplet Type × OCI), the trajectory of statistical learning (Time × Triplet Type × OCI-12 score). Moreover, OCI-12 scores did not modulate the relationship between cognitive flexibility (Perseverative error × Triplet Type × OCI-12 score, see: Figure 1) and the dynamics of statistical learning in the present study (Perseverative error × Time × Triplet Type × OCI-12 score).

Table 1. Results of the Linear Mixed-Effects Model predicting blockwise median Reaction Time

Effect	*df*	*F*	*p*
Time	1, 399.98	125.06	**< .001**
Triplet Type	1, 11297.07	169.21	**< .001**
OCI-12 score	1, 400.01	3.15	.077
Perseverative error	1, 400.02	7.31	**.007**
Time × Triplet Type	1, 11297.10	10.42	**.001**
Time × OCI-12 score	1, 399.88	0.15	.699
Triplet Type × OCI-12 score	1, 11297.11	0.00	.926
Time × Perseverative error	1, 400.07	3.13	.078
Triplet Type × Perseverative error	1, 11297.07	0.44	.508
OCI-12 score × Perseverative error	1, 400.01	0.26	.600
Time × Triplet Type × OCI-12 score	1, 11297.18	0.09	.763
Time × Triplet Type × Perseverative error	1, 11297.1	0.92	.338
Time × OCI-12 score × Perseverative error	1, 400.00	3.61	.058
Triplet Type × OCI-12 score × Perseverative error	1, 11297.09	1.29	.257
Time × Triplet Type × OCI-12 score × Perseverative error	1, 11297.15	0.67	.412

Note. The table summarizes all main effects and interactions. Degrees of freedom *(df)* correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results ($p < .05$) are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type (High vs. Low) was significant (b = -5.87, SE = 0.45, z = -13.01, $p < .001$, 95% CI [-6.76, -4.99]), indicating faster responses to high- than to low-probability triplets. Time was also significant (b = -1.1, SE = 0.10, z = -11.18, $p < .001$, 95% CI [-1.29, -0.9]), showing that RT decreased as the task progressed. Statistically significant Perseverative Error indicated that more perseverative errors were associated with slower reaction times (b = 1.44, SE = 0.53, z = 2.70, p = .007, 95% CI [0.4, 2.49]). The significant Time × Triplet Type interaction (b = -0.34, SE = 0.10, z = -3.23, p = .001, 95% CI [-0.54, -0.13]) reflected gradual improvement in statistical learning over time. Time was treated as a continuous variable in all analyses; however, for the post hoc analyses, it was segmented into three time points ($Block_5$, $Block_{10}$, $Block_{15}$). $Block_5$ (b = -4.86, SE = 0.55, z = -8.84, $p < .001$, 95% CI [-5.94, -3.78]), $Block_{10}$ (b = -6.55, SE = 0.50, z = -13.16, $p < .001$, 95% CI [-7.52, -5.57]), and $Block_{15}$ (b = -8.24, SE = 0.86, z = -9.58, $p < .001$, 95% CI [-9.92, -6.55]). Sidak-adjusted pairwise comparisons revealed significant differences in statistical learning (High vs. Low differences) between $Block_5$–$Block_{10}$ (b = 1.69, SE = 0.52, z = 3.23, p = .004), $Block_5$–$Block_{15}$ (b = 3.37, SE = 1.05, z = 3.23, p = .004), and $Block_{10}$–$Block_{15}$(b = 1.69, SE = 0.52, z = 3.23, p = .004).

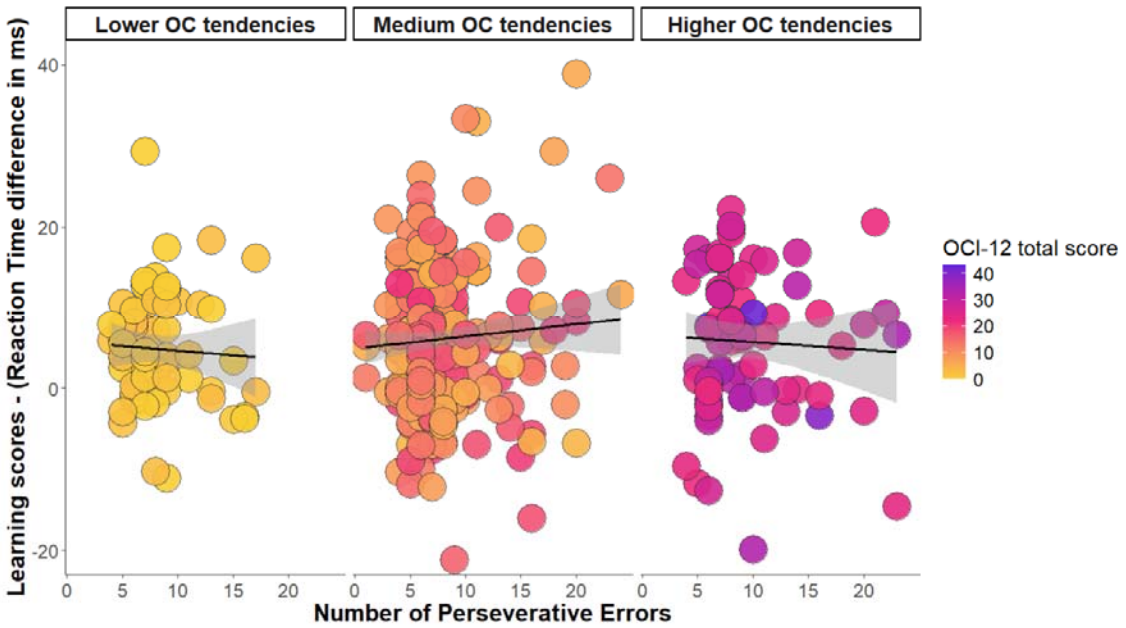


Figure 1. The figure illustrates the relationship between cognitive flexibility, as measured by the Number of Perseverative errors on the Card Sorting Task along the x-axis, and statistical learning performance along the y-axis, which is operationalized as the difference in reaction time between high- and low-probability triplets. Each point represents an individual participant, with color encoding their total OCI-12 score along a continuous gradient from low (yellow) through intermediate (pink) to high (purple) obsessive-compulsive tendencies. A linear regression line with 95% confidence intervals is overlaid in black. While the OCI-12 score was treated as a continuous variable in all statistical analyses, for visualization purposes, the data are faceted by the levels of OC tendencies. These levels represent varying degrees of OCI-12 scores, approximating one standard deviation below the mean (Lower OC tendencies), at the mean (Medium OC tendencies), and one standard deviation above the mean (Higher OC tendencies), respectively. The color gradient used in the plot (yellow to pink to purple) visually reflects this increase in the level of OC tendencies. No relationship was observed between cognitive flexibility and RT-based statistical learning, and this pattern was consistent across the level of OC tendencies.

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

We performed a linear mixed-effects model on blockwise mean accuracy of the ASRT task, with fixed effects for Time (Block 1-15), Triplet Type (high- vs. low-probability), OCI-12 score, Number of Perseverative errors of the Card Sorting Task, and all higher-order interactions. Random effects included participant-specific intercepts and correlated slopes for Time and Triplet Type to account for individual variability. The statistical parameters underlying the effects reported above are summarized in Table 2, whereas the full set of statistical estimates (b, SE, 95% CI, t, df, and p values) is provided in Supplementary Table S2.

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

Cognitive flexibility influenced performance: a higher number of Perseverative errors were associated with lower overall accuracy (main effect of Perseverative error), and a modest decline in visuomotor performance over time (Time × Perseverative error). Moreover, a significant Triplet Type × Perseverative error interaction revealed an antagonistic relationship between statistical learning and cognitive flexibility (Triplet Type × Perseverative error), with greater statistical learning linked to reduced cognitive flexibility, that is higher number of perseverative errors: ($b_{\text{Low perseverative errors}}$ = 1.95, 95% CI [1.59, 2.30]; $b_{\text{Mean perseverative errors}}$ = 2.22, 95% CI [1.97, 2.47]; $b_{\text{High perseverative errors}}$ = 2.50, 95% 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% CI [−0.53, −0.02], p = .034; $b_{\text{Low perseverative errors} - \text{High perseverative errors}}$ = −0.55, 95% CI [−1.06, −0.04], p = .034; $b_{\text{Mean perseverative errors} - \text{High perseverative errors}}$ = −0.28, 95% CI [−0.53, −0.02], p = .034). Thus, individuals with poorer cognitive flexibility (higher numbers of perseverative errors) exhibited enhanced statistical learning, except when considering the trajectory of learning (Time × Triplet Type × Perseverative error), where this pattern was less pronounced.

OC tendencies did not significantly influence overall accuracy (main effect of OCI-12 score), visuomotor performance (Time × OCI-12 score), statistical learning (Triplet Type × OCI-12 score), or its improvement over time (Time × Triplet Type × OCI-12 score). Similarly, no interactions were observed between OC tendencies and Perseverative errors for overall accuracy or visuomotor performance (Time × Perseverative error × OCI-12 score). However, a significant Triplet Type × Perseverative error × OCI-12 score interaction indicated that OC tendencies modulate the antagonistic relationship between statistical learning and cognitive flexibility (see: Figure 2). 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 were positively associated with statistical learning, with a significant slope (b = 0.145, SE = 0.048, z = 2.97, 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, p = .034), suggesting that poorer cognitive flexibility was linked to enhanced statistical learning among lower and medium level of OC tendencies. In contrast, this association disappeared among individuals with higher OC tendencies, where the slope was non-significant (b = −0.006, SE = 0.040, z = −0.17, p = .862). Overall, statistical learning increased as the number of perseverative errors rose for individuals with lower to medium OC tendencies, reflecting an antagonistic pattern in which reduced cognitive flexibility was accompanied by better statistical learning. This antagonistic pattern weakened in participants with high OC tendencies, where statistical learning remained moderate regardless of cognitive flexibility. Importantly, this modulation was not observed when examining the full trajectory of learning over time (Triplet Type × Time × Perseverative error × OCI-12 score).

Table 1. Results of the Linear Mixed-Effects Model predicting blockwise mean accuracy

Effect	*df*	*F*	*p*
Time	1, 400.22	58.82	**< .001**
Triplet Type	1, 400.14	302.7	**< .001**
OCI-12 score	1, 399.97	0.00	.976
Perseverative error	1, 400.06	6.18	**.013**
Time × Triplet Type	1,10898.51	33.15	**< .001**
Time × OCI-12 score	1, 400.05	0.01	.935
Triplet Type × OCI-12 score	1, 399.91	0.89	.347
Time × Perseverative error	1, 400.39	4.41	**.036**
Triplet Type × Perseverative error	1, 400.52	4.48	**.035**
OCI-12 score × Perseverative error	1, 400.03	0.91	.341
Time × Triplet Type × OCI-12 score	1, 10898.03	0.98	.321
Time × Triplet Type × Perseverative error	1, 10899.01	0.04	.845
Time × OCI-12 score × Perseverative error	1, 400.26	2.30	.130
Triplet Type × OCI-12 score × Perseverative error	1, 400.30	6.21	**.013**
Time × Triplet Type × OCI-12 score × Perseverative error	1,10898.65	1.81	.178

Note. The table summarizes all main effects and interactions. Degrees of freedom *(df)* correspond to Satterthwaite approximations. *F* = F-statistic; *p* = significance value. Statistically significant results *(p < .05)* are shown in bold. Significant main effects were followed up with post hoc comparisons: The main effect of Triplet Type indicated higher accuracy for high- than for low-probability triplets (b = 2.22, SE = 0.13, z = 17.40, p < .001, 95% CI [1.97, 2.47]). Time was also significant (b = -0.15, SE = 0.02, z = -7.67, p < .001, 95% CI [-0.18, -0.11]), showing that accuracy decreased as the task progressed. The main effect of Perseverative error indicated that more perseverative errors were associated with lower accuracy (b = -0.11, SE = 0.04, z = -2.49, p = .013, 95% CI [-0.2, -0.02]) . Time × Triplet Type interaction revealed improvement in statistical learning over time. Time was treated as a continuous variable in all analyses; however, for the post hoc analyses, it was segmented into three time points ($Block_5$, $Block_{10}$, $Block_{15}$). $Block_5$ (b = 1.75, SE = 0.15, z = 11.56, p < .001, 95% CI [1.46, 2.05]), $Block_{10}$ (b = 2.54, SE = 0.14, z = 18.26, p < .001, 95% CI [2.26, 2.81]), and $Block_{15}$ (b = 3.32, SE = 0.23, z = 14.48, p < .001, 95% CI [2.87, 3.77]). Sidak-adjusted pairwise comparisons revealed significant differences between $Block_5$–$Block_{10}$ (b = -0.78, SE = 0.52, z = 3.23, p = .004), $Block_5$–$Block_{15}$ (b = -1.57, SE = 1.05, z = 3.23, p = .004), and $Block_{10}$–$Block_{15}$ (b = -0.78, SE = 1.05, z = 3.23, p = .004). For the Time × Perseverative Error interaction, Sidak-adjusted pairwise comparisons showed significant declines over time at lower perseverative error levels (b = -0.11, SE = 0.03, z = -3.92, p < .001, 95% CI [-0.16, -0.05]; b = -0.15, SE = 0.02, z = -7.67, p < .001, 95% CI [-0.18, -0.11]) and at higher perseverative error levels (b = -0.19, SE = 0.03, z = -6.79, p < .001, 95% CI [-0.24, -0.13]), indicating a decline in visuomotor performance over time. Perseverative Error was treated as a continuous variables in all primary analyses; however, for the post hoc analyses they were depicted in three categories (M–SD, M, M+SD).

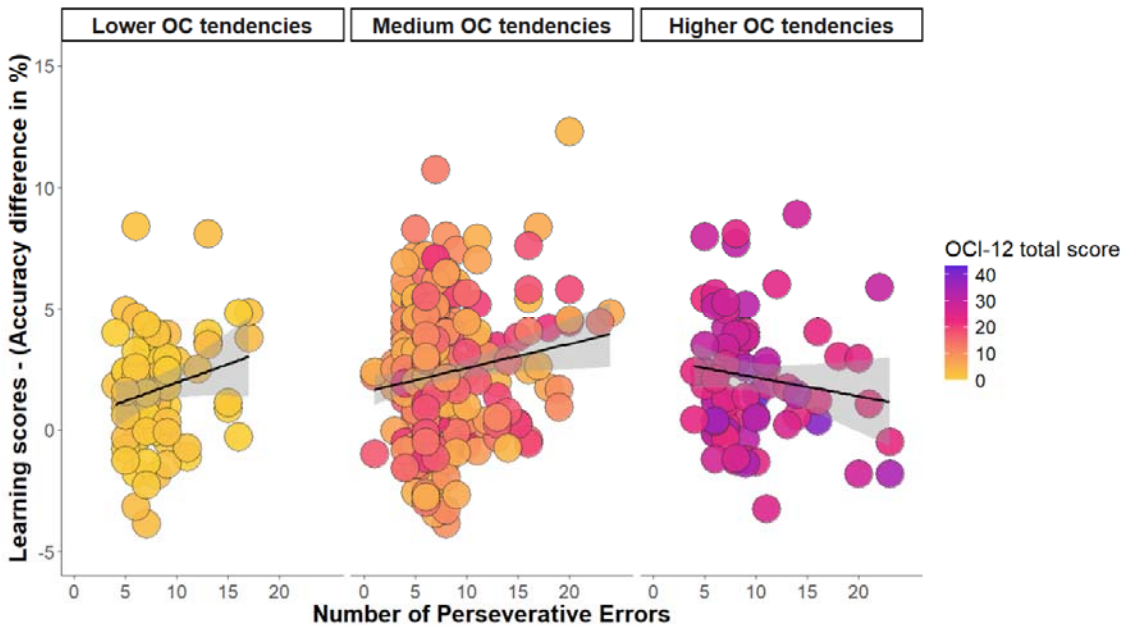


Figure 2. The figure illustrates the relationship between cognitive flexibility, as measured by the number of perseverative errors on the Card Sorting Task along the x-axis, and statistical learning performance along the y-axis, which is operationalized as the difference in accuracy between high- and low-probability triplets. Each point represents an individual participant, with color encoding their total OCI-12 score along a continuous gradient from low (yellow) through intermediate (pink) to high (purple) obsessive-compulsive tendencies. A linear regression line with 95% confidence intervals is overlaid in black. While the OCI-12 score was treated as a continuous variable in all statistical analyses, for visualization purposes, the data are faceted by the levels of OC tendencies. These levels represent varying degrees of OCI-12 scores, approximating one standard deviation below the mean (Lower OC tendencies) at the mean (Medium OC tendencies), and one standard deviation above the mean (Higher OC tendencies), respectively. The color gradient used in the plot (yellow to pink to purple) visually reflects this increase in the level of OC tendencies. The figure highlights the moderating role of OC tendencies in the antagonistic association between statistical learning and cognitive flexibility. Specifically, the typical inverse relationship, where reduced cognitive flexibility is associated with enhanced statistical learning, was observed in participants with Lower and Medium OC tendencies. In contrast, this pattern was not present among individuals with Higher OC tendencies, for whom statistical learning remained relatively stable across the cognitive flexibility continuum. This suggests a disruption of the typical trade-off between these cognitive functions in the context of OC tendencies.

Discussion

In this study, we addressed a critical gap in understanding the relationship between goal-directed and automatic behaviour by examining how unsupervised SL interacts with cognitive flexibility. We specifically investigated how this relationship is modulated by OC tendencies within a non-clinical adult population with a focus on stable, trait-related organizational strategies in cognitive processing. We conducted online experiments on an undiagnosed 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 with the Card Sorting Task. Our findings corroborate previous theories indicating a competitive interaction between SL and executive functions, specifically cognitive flexibility. Crucially, we found that this inverse relationship progressively

weakened as OC tendencies increased, suggesting that, even at undiagnosed levels, OC tendencies can disrupt the optimal balance between SL and goal-directed functions.

Our results build upon existing theories that highlight a disruption between automatic and goal-directed processes in both clinical OCD and subclinical OC tendencies or compulsivity [8–12,23,26] In particular, the typical antagonistic relationship between these functions, as emphasized by competitive memory system frameworks [6,34,37–39,41,42,56,57] appears to weaken with increasing levels of non-clinical OC tendencies. This pattern may appear partly inconsistent with the habit hypothesis [8,9,26,58,59], which primarily predicts a context-dependent shift toward habitual control. However, methodological differences may partly account for these discrepancies since they predominantly employed outcome devaluation or contingency degradation paradigms, typically assessing learning after extended instrumental training and evaluating goal-directed behavior based on participants' ability to adapt to altered rules and feedback within a single experimental context [8,9,26]. Such paradigms require the simultaneous integration of multiple neurocognitive processes under high cognitive demand, which may bias performance toward habitual responding. In contrast, the present study indicates that higher OC tendencies are associated with reduced cognitive flexibility, constraining statistical learning rather than enhancing. From this perspective, the observed interplay between SL performance and cognitive flexibility at higher levels of undiagnosed OC tendencies represents task-specific interference and reflects a stable organizational characteristic of behavioral adaptation across contexts.

Taken together, these findings suggest that the pattern observed at the trait level diverges from the state-dependent bias toward habitual responding described in prior work, raising the possibility of a dissociation between transient task-related effects and more stable neurocognitive organization across the OC spectrum. Whereas state-level paradigms have primarily revealed increased reliance on habitual control under high cognitive demand [8,9,26], the present results indicate that increasing OC tendencies are associated with a weakening of the relationship between executive control and statistical learning. Thus, individuals with weaker executive functions, specifically reduced cognitive flexibility, demonstrate enhanced acquisition of environmental statistical regularities at lower levels of OC tendencies, whereas at higher levels, the same reduction in flexibility is associated with impaired SL. We can speculate that the interaction between SL and cognitive flexibility may reflect an individual's position along the OC continuum: at lower levels of OC tendencies, reduced flexibility may facilitate the efficient extraction of statistical regularities, whereas at higher levels, increased rigidity appears to constrain learning. More broadly, these findings suggest that as OC tendencies increase, the typical antagonism between SL and executive functions may become attenuated, such that automatic functions are less able to compensate for diminished flexibility. Elucidating this potential dissociation will require future research to disentangle trait-level and state-dependent contributions to this interaction and to determine how it shapes the balance between learning mechanisms and executive control across the OC spectrum.

Beyond demonstrating a trait-dependent interaction between neurocognitive systems, our findings address an important gap by elucidating the interaction between unsupervised learning, a primary form of learning [30], and executive functions among OC tendencies. Consistent with prior findings, unsupervised learning was found to be preserved [20,60–63] suggesting this core learning mechanism remains robust across OC tendencies similar to

OCD, although not all prior findings are fully aligned with this pattern [64–68]. This preservation is particularly noteworthy, as the excessive bias toward habitual behaviour in OCD may partly stem from external reward-driven learning. In feedback- or reward-driven contexts, it is difficult to disentangle whether performance improvements reflect sensitivity to external reinforcement or strengthened stimulus–response associations. Moreover, individuals with OCD and OC tendencies may reach a ceiling effect more rapidly due to heightened reward or feedback sensitivity, thereby accelerating the shift toward enhanced automatic processes and reducing the opportunity for flexible behavioral adaptation. Although the pure learning mechanism remained intact, the interaction of SL with goal-directed functions became atypical among higher OC tendencies. This suggests that the disruption lies not within the pure learning mechanisms themselves, but in the dynamic interplay between these systems among OC tendencies and possibly, in OCD [9,26,29,69.] Future research should further investigate the state-dependent interaction between habitual and goal-directed processes in relation to unsupervised learning mechanisms, particularly in the absence of external reward. This would clarify the fundamental relationship between habitual and goal-directed functions and their contribution to OC- and OCD-related behavioral manifestations.

On the other hand, previous approaches emphasizing impairments in goal-directed or executive functions in OCD have primarily examined these processes as distinct functional domains [43,60,61,65,72,74], without sufficiently considering how these alterations emerge within a broader neurocognitive network. In contrast, our findings align with the perspective that neither habitual, automatic functions 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 [8,9,19,71,77,79]. But unlike a previous study, which measured generative cognitive flexibility and assessed habitual tendencies via self-report questionnaires [19], our study specifically examined reactive cognitive flexibility, which a recent meta-analysis has challenged as being independently impaired in OCD [70]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 [9,11,19,26,59]. Alongside theoretical frameworks that propose a bias toward automatic processes in clinical OCD [9,10,19,25,26,29,59,71] other perspectives emphasize the potential emergence of compensatory mechanisms, wherein impairments in implicit learning are offset by increased engagement of controlled, explicit processes to maintain effective performance [36,60,61,64,73,75] These findings were supported by both behavioral and neuroimaging evidence, showing that during unsupervised behavioral tasks [60,61] neural activity was predominantly associated with hippocampal and medial temporal lobe regions rather than striatal structures [62,63] 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 [9,60,61,64,73,75]. 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.

Another noteworthy finding is that the unrevealed interplay with cognitive flexibility appeared only in the accuracy-based performance indicator of the ASRT task. This dissociation is particularly interesting as it raises the question of which performance components are more sensitive to OC tendencies. One possible explanation is that the card-sorting task relies on accuracy without imposing temporal constraints [48]. Accuracy- and rule-based learning generally require more effortful processing [76,78,80], which may account for the antagonistic relationship between the two measures. Specifically, enhanced implicit adaptation to rule-based structures may come at the cost of reduced performance in tasks requiring explicit rule detection, an effect that aligns with the competition and cooperation framework outlined above [6,34,38,39,41,57]. This pattern also reflects the clinical features of OCD, where symptoms often involve an excessive focus on order, regularity, and precision, such as checking, arranging, or striving for symmetry [7,81]. Consequently, accuracy-based measures may be especially sensitive to the influence of OC tendencies. Taken together, these findings suggest that OC symptoms may interfere more strongly with learning processes grounded in precision and rule detection, offering a clearer picture of how cognitive rigidity manifests in the disorder.

It is important to note that our study was conducted on an undiagnosed, so-called non-clinical population of healthy adults. Therefore, while findings from clinical OCD research provide an important theoretical background, our results should not be generalized to clinical OCD populations but rather interpreted within a transdiagnostic framework. At the same time, spectrum-based approaches offer valuable theoretical and methodological contributions to the deeper understanding of clinical conditions, including the characteristics of OCD [11,13,20,22,24,82]. Importantly, previous research has demonstrated that OC tendencies can influence a broad range of neurocognitive functions, including statistical learning [20]inhibitory control [83], cognitive flexibility[19],and decision-making [84,85] This can prove that this approach serves as an effective methodological tool for identifying individual differences in neurocognitive functions. The current study contributes to this growing body of literature by highlighting how OC tendencies may influence not just cognitive domains in isolation but the dynamic interplay between them, offering a more integrated understanding of the neurocognitive profile associated with OC tendencies. Our findings indicate that while a dynamic interplay among neurocognitive functions is maintained at lower levels of OC tendencies, this interaction may potentially be absent in 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 functions 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 [20,57,82,86–88], may have affected the generalizability of the findings. Although rigorous data quality checks were essential to obtain high-quality data, the inclusion criterion requiring the absence of any self-reported psychiatric or neurological history likely limited the representation of individuals with more pronounced OC tendencies. As a result, the upper range of the OC spectrum may have been underrepresented, potentially narrowing the scope of our conclusions. We did not control for other conditions that are frequently associated with elevated compulsivity and are often comorbid with OC tendencies, including anxiety and depressive symptomatology [11,89,90]. Consequently, the present results do not allow us to fully isolate effects specifically related to the OC symptom dimension from those potentially driven by related affective or psychopathological factors. Presenting the tasks in a fixed order may have introduced potential order or fatigue effects. Future studies should therefore consider counterbalancing task order to minimize such influences, as performance on later tasks may be affected by declining attention or cognitive fatigue. In addition, no attention checks were included during the administration of the OCI-12 questionnaire, which may have increased the likelihood of inattentive responding [91]. Moreover, although cognitive flexibility was assessed using a card sorting task, this measure has inherent methodological limitations [92,93]. Therefore, future research would benefit from incorporating multiple measures of cognitive flexibility to obtain a more comprehensive assessment of executive functioning. Finally, the present study was conducted in a university-based adult sample, which may limit the generalizability of the findings to the broader population. Accordingly, future studies should extend these investigations to more diverse age groups and community samples to strengthen external validity.

To conclude, our results support the competitive memory systems hypothesis, that emphasize an antagonistic relationship between neurocognitive systems [6,34,37,41,42] by elucidating a more general, trait-dependent dynamic interplay between SL and goal-directed processes, here cognitive flexibility, and how their interaction is modulated by the prevalence of OC tendencies in a non-clinical population. While lower prevalence of OC tendencies may facilitate adaptive neurocognitive interactions, higher OC tendencies might represent early neurocognitive markers predictive of increased vulnerability to OCD. These results underscore the significance of conceptualizing OC tendencies as transdiagnostic traits to enhance early identification and inform tailored interventions. Importantly, our study highlights the necessity for cognitive neuroscience to transcend the examination of isolated neurocognitive functions and instead prioritize the investigation of their interactive dynamics, as the integrity of individual processes alone may mask critical dysfunctions emerging from their interactions.

Resource availability

Lead contact

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

Materials availability

This study did not generate new unique reagents.

Data availability statement

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

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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.

Declaration of generative AI and AI-assisted technologies in the writing process

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

STAR METHODS

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

A total of 568 university students took part in the study through an online experiment in exchange for course credit. The sample shows partial participant overlap with those reported

in Brezóczki et al. [20]Hann et al. [94], and Nagy et al. [86]; however, the datasets are not identical, as data were collected across multiple studies with different primary research aims and measurement protocols. To maintain data integrity, rigorous quality control procedures were implemented, resulting in the exclusion of 164 participants who failed to follow the instructions. Our goal was to meet multiple data quality criteria, which are outlined in detail in the 'Quality control of the data' section below. The final sample consisted of 404 participants (285 female, 111 male, and 3 non-specified; M_{Age} *= 22.06 years;* SD_{Age} *= 5.09).* This study did not perform analyses based on sex or gender, which could limit the generalizability of the findings. Participants provided informed consent, and the studies received approval from the Research Ethics Committee of Eötvös Loránd University, Budapest, Hungary (2021/504), following the principles of the Declaration of Helsinki.

METHOD DETAILS

Alternating Serial Reaction Time task

Statistical learning was measured by the Alternating Serial Reaction Time (ASRT) task [45,46]. The task was implemented in JavaScript using jsPsych version 6.1.0 [95] . Each trial presented a visual stimulus, an illustration of a dog's head, in one of four horizontally aligned screen positions (Figure 3A). 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 3B). 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 3C). 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, but not on their statistical learning performance. Still, no information was provided about their statistical learning performance, as they were unaware that the task involved detecting a hidden regularity.

Card Sorting Task

Cognitive flexibility was assessed using the Card Sorting Task (CST), adapted from the Wisconsin Card Sorting Test (WCST), a well-established measure of executive function [48,96,97] The CST evaluates an individual's ability to shift cognitive strategies in response to changing task demands. During the task, four reference cards are displayed simultaneously on the screen. Each card contains visual stimuli that differ along three dimensions: color (red, yellow, green, or blue), quantity (one to four items), and shape (triangle, star, diamond, or circle). In each trial, a separate target card appears beneath the reference cards (Figure 3D). Participants are instructed to match the target card with one of the four reference cards according to a common feature, either color, quantity, or shape, by selecting the corresponding card. Importantly, the correct matching rule is not disclosed to the participant. Instead, participants are required to infer the rule based on feedback provided after each response, which indicates whether the selected card was correct or incorrect (Figure 3E). 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.

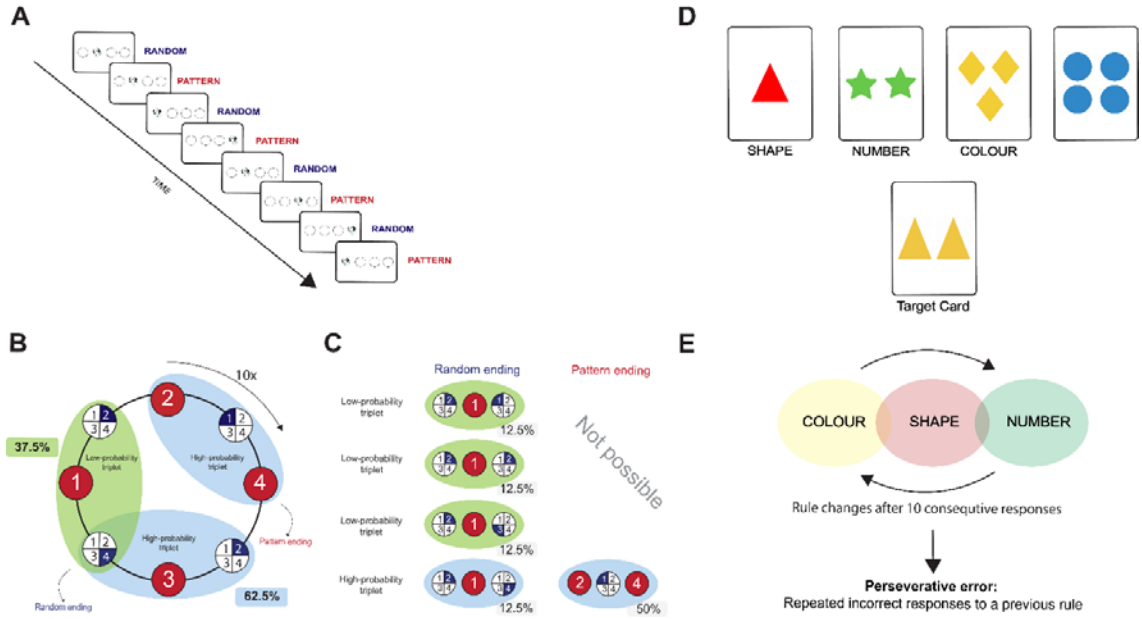

Figure 3. Design of the Study. (A) In the Alternating Serial Reaction Time (ASRT) task, participants were instructed to respond by pressing keys corresponding to the spatial location of a target stimulus, depicted as a dog's head. Each trial followed an eight-element probabilistic sequence composed of alternating pattern and random elements. For example, a sequence such as 2–r–4–r–3–r–1–r consisted of fixed pattern trials at positions 2, 4, 3, and 1 (from left to right), interleaved with random elements, denoted by 'r', which could appear at any of the four possible locations. **(B)** Each trial was considered the third element in a sequence of three consecutive trials (a triplet). Pattern elements, which consistently appeared in fixed positions throughout the task, were displayed with red backgrounds, whereas random elements, selected randomly from the four possible locations, were shown with blue backgrounds. The structure of the sequence resulted in certain triplets occurring more frequently than others. These were categorized as high-probability triplets, while less frequent combinations were defined as low-probability triplets. **(C)** For illustrative purposes, three triplets are highlighted: 2(P)–1(R)–

4(P), a pattern-ending high-probability triplet; 2(R)–3(P)–4(R), a random-ending high-probability triplet; and 4(R)–1(P)–2(R), a random-ending low-probability triplet. High-probability triplets could occur in one of two ways: either with two pattern trials and a random trial in the middle (accounting for 50% of all trials), or with two random trials and a pattern trial in the middle (accounting for 12.5% of trials). Overall, 62.5% of trials constituted the final element of a high-probability triplet, whereas the remaining 37.5% served as the final element of a low-probability triplet. **(D)** Schematic illustration of the Card Sorting Task (CST). Four reference cards are presented simultaneously, differing along three stimulus dimensions (color, shape, and quantity). On each trial, a target card appears below the reference cards, and participants are instructed to match it to one of the reference cards according to an sorting rule. **(E)** The rules are presented in a fixed, repeating order for up to six categories: Color, Shape, Number. The sorting rule changes after ten consecutive correct responses. Cognitive flexibility is indexed by the number of perseverative errors, defined as continued application of a previously correct but currently invalid rule.

Obsessive-Compulsive Inventory

Obsessive-compulsive tendencies were assessed using the 12-item version of the Obsessive-Compulsive Inventory (OCI-12, [98,99]), a self-report questionnaire measuring the severity of symptoms on a 5-point Likert scale ranging from 0 (not at all) to 4 (extremely). Participants reported how much each symptom had bothered them during the previous month. The OCI-12 has demonstrated strong psychometric validity, including high internal consistency and test-retest reliability, in both clinical and non-clinical samples [98]. The Cronbach's alpha in our sample indicated good internal consistency ($\alpha = 0.89$). The total score can vary from 0 to 48. In our final sample, the observed scores ranged from 0 to 43 ($M = 12.58$; $SD = 9.02$); see Figure 4. For reference, the full 18-item OCI-R was also administered and is provided in the Supplementary Materials.

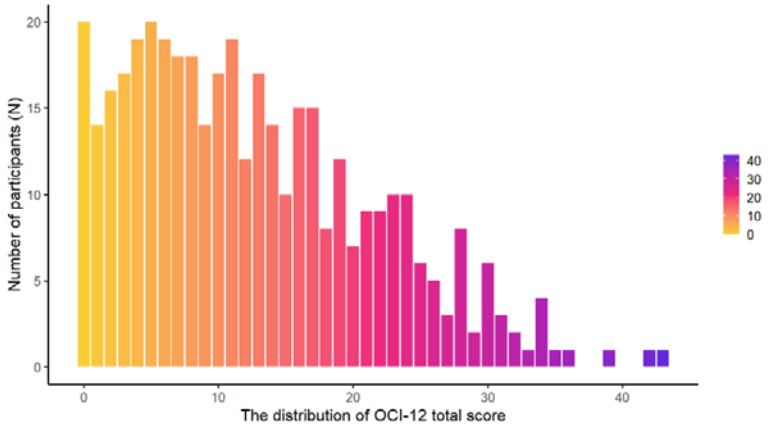

Figure 4. The distribution of the participants' OC tendencies as measured by the OCI-12 total score in the sample. The x-axis indicates the total OCI-12 score, while the y-axis indicates the number of participants. The color gradient transitions from yellow, through pink, to purple, reflecting increasing levels of OC tendencies.

Procedures

The experiment was conducted using the Gorilla Experiment Builder platform (https://www.gorilla.sc) [100]. 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 [34,101] Following the ASRT task, cognitive flexibility was evaluated using the CST, and obsessive-compulsive tendencies were measured with the OCI-12. 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

Online data collection is known to present several methodological challenges, as outcomes may be influenced not only by the psychological constructs of interest but also by variability in participants' response styles, engagement levels, and task completion strategies [91]. To address these concerns, we implemented data quality control procedures following established recommendations for online experimental research [88]. 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) performed their mean raw accuracy on the ASRT task was below 80%, as such low performance was considered indicative of insufficient task engagement rather than genuine performance (N = 24, 4.23%); 5) 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) took long self-paced breaks between ASRT blocks, as such extended interruptions may indicate reduced task engagement (N = 4, 0.7%), 9) random buttom pressing during ASRT task (N = 3, 0.53%) and 10) participants who scored in the zero category on the CST, indicating random clicking during the task or incomplete understanding of it (N = 19, 3.34%). As some participants met multiple exclusion criteria, the combined criteria resulted in the exclusion of a total of 164 participants (28.87%).

QUANTIFICATION AND STATISTICAL ANALYSIS

Data preparation and analysis

Data preprocessing, statistical analysis, and visualization were carried out in R version 4.4.2 [102] For the ASRT task, each trial was categorized according to whether it represented the final element of a high- or low-probability triplet. Only the first response for each trial was retained; subsequent responses were excluded to ensure response validity. Trials with reaction times (RTs) below 150 ms or above 1000 ms, as well as those falling beyond three absolute median deviations from each participant's median RT, were removed to control for outliers (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 [34,103]. The first two trials of each block were also removed, as they did not complete a triplet structure. Furthermore, incorrect responses were excluded from RT analyses. Following these procedures, 17.54% of trials were excluded from accuracy analyses and 24.61% from RT analyses. These exclusion rates are consistent with those reported in online ASRT studies [20,57,82,86,87].

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

Post hoc analyses involved the computation of estimated marginal means and marginal trends for simple effects and simple slopes, utilizing the emmeans package [105]. Significant interactions involving continuous predictors, specifically the OCI-12 score and Perseverative errors, were probed at three levels: the mean, as well as at ±1 standard deviation from their means. For the Time factor, probing was performed at the end of the 5th, 10th, and 15th blocks. Figures were created with 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-12 score as a continuous variable for all our analyses, for more illustrative data visualization and clarified post hoc analysis, we depicted results at lower OC tendencies (Mean OCI-12 score - SD), medium OC tendencies (Mean OCI-12 score) and higher OC tendencies (Mean OCI-12 score + SD), based on standard deviations from the mean. For the

more complex interactions, the same approach was applied to the Number of Perseverative errors.

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

Reaction time:
*MedianRT ~ Time * Triplet Type * OCI-12 score * Perseverative error + (Time | Participant)*

Accuracy:
*MeanAccuracy ~ Time * Triplet Type * OCI-12 score * Perseverative error + (Time + Triplet Type | Participant)*

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