A functional trade-off between executive control and implicit statistical learning is dynamically gated by mind wandering

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Abstract

Human cognition must balance goal-directed behavior with the need to learn from environmental regularities. Mind wandering (MW), a state of attentional decoupling from the task at hand, is paradoxically associated with both executive failures and enhanced implicit statistical learning, yet the direct relationship between these phenomena remains unclear. Here, we provide direct behavioral evidence for a functional trade-off between these competing demands. Using a task that concurrently measured response inhibition, statistical learning, and self-reported task focus, we show that MW is associated with impaired inhibitory control but enhanced learning of probabilistic sequences. Critically, we reveal that these effects are mechanistically linked: the magnitude of the learning enhancement during MW is quantitatively modulated by the efficacy of response inhibition. These findings demonstrate that transient lapses in top-down executive control directly facilitate the implicit extraction of environmental statistics, supporting neurocompetition models and framing MW as a cognitive state that may be evolutionarily preserved to promote the unsupervised acquisition of predictive models.

Keyword: mind wandering, statistical learning, response inhibition, predictive processing

Introduction

Mind wandering (MW) occurs when attention shifts away from the task at hand, and our thoughts drift towards internal reflections about the past or future. This state is typically linked to reduced cognitive performance in areas such as sustained attention (Seli et al., 2015), executive control (Andrillon et al., 2021; McVay & Kane, 2012), reading comprehension (McVay & Kane, 2012), model-based decision-making (Liu et al., 2023), and fluid intelligence (Mrazek, Smallwood, & Schooler, 2012; Mrazek, Smallwood, Franklin, et al., 2012). This is often evidenced by lower accuracy and quicker, more impulsive responses (Mooneyham & Schooler, 2013), suggesting a decline in cognitive control. Despite these drawbacks, humans spend a significant portion of their time in a MW state (Bastian & Sackur, 2013; Cheyne et al., 2009; Mooneyham & Schooler, 2013). This suggests that MW might serve some adaptive purpose. Recent studies show that MW can provide cognitive benefits, particularly under low attentional demands and when the goals of learning are opaque or fully implicit (Amer et al., 2016; Thompson-Schill et al., 2009), such as in the case of statistical learning (Simor et al., 2025; Vékony et al., 2025). However, the exact mechanism behind this benefit remains unclear. Here, we test the hypothesis that the transient state of executive failure during MW is associated with the implicit extraction of statistical regularities from the environment. To arbitrate this, we employ a paradigm designed to simultaneously capture the dynamics of MW, response inhibition, and statistical learning, thereby offering a unified account of the cognitive trade-offs between endogenous thought and statistical learning.

Research has shown that MW significantly impacts executive functioning, including response inhibition, which governs quick behavioral action restriction or action cancellation (Kam & Handy, 2014; Maillet et al., 2020). This effect often manifests as an inability to stop a prepotent response, indicating that top-down control has temporarily broken down. Despite its deleterious impact on executive functions, MW was repeatedly shown to enhance our ability to discern complex statistical patterns in our environment. A paradox lies at the heart of human cognition: attenuated executive control is associated with both the rise of MW (Randall et al., 2014) and enhanced statistical learning (Simor et al., 2025; Vékony et al., 2025). This raises the possibility of a shared underlying mechanism. The two-sided nature of MW (marked by a negative association with executive control and a positive one with statistical learning) aligns with both theoretical considerations and empirical findings

supporting the neurocompetition model (Ambrus et al., 2020; Nemeth et al., 2013; Smalle et al., 2017; Virag et al., 2015). This model posits that effortful, controlled processes and implicit, associative, and habitual learning compete for shared neurocognitive resources. Although the neurocompetition model has inspired a range of studies, empirical evidence for competition between cognitive processes remains largely indirect: executive functions, statistical learning, and their associations with MW are typically examined in separate tasks. The critical question of whether the attentional deficits associated with MW are accompanied by corresponding gains in implicit statistical learning can only be addressed by a single, integrated task to enable assessing the interplay between these cognitive phenomena on an intra-individual level. Here, we provide a direct empirical exploration of this complex interplay, aiming to elucidate the dynamics between these fundamental cognitive processes.

Healthy participants completed the Cognitive Trade-off Task (CTT), a combined inhibition and statistical learning task with thought probes inserted between task blocks. Consistent with prior work, our results confirm that periods of MW are characterized by compromised response inhibition and enhanced extraction of statistical regularities. Our principal novel finding, however, is the direct link between these phenomena. We show that response inhibition quantitatively modulates the relationship between MW and statistical learning. This suggests a functional trade-off, where the transient lapse in top-down executive control during MW facilitates the implicit statistical learning of environmental patterns.

Methods

Participants

Three hundred and seventeen university students (249 females) were enrolled in the study. The mean age of the participants was 22.02 ± 4.12 SD years. After exclusions (see "*Quality control of the data*" section), two hundred and forty participants remained in the final sample. Participants received course credit for taking part in the study. Participants provided informed consent before enrolling. The experiment was conducted in accordance with the Declaration of Helsinki.

Quality control of the data

Data integrity was ensured through a quality control examination (Rodd, 2024) based on predefined criteria (similar to Vékony et al., 2025). Participants were excluded if they

reported a history of neurological or psychiatric disease (*n* = 43), use of nervous system-affecting medication (*n* = 8), alcohol consumption within three hours before the experiment (*n* = 19), or prior completion of the task (*n* = 10). Additionally, those who showed extreme non-compliance were disqualified on the basis that (1) task accuracy was less than 80% (*n* = 11), (2) task completion duration was greater than 50 minutes (*n* = 7), or (3) task restart occurred at any moment (*n* = 3). Seventy-seven individuals were excluded, some of whom satisfied more than one exclusion criterion.

The Cognitive Trade-off Task (CTT)

The CCT is based on the Alternating Serial Reaction Time (ASRT) task (Howard & Howard, 1997), incorporating certain 'No-Go' trials to which participants must refrain from responding. The experimental task was programmed in JavaScript using the jsPsych library v.6.1.0 (de Leeuw, 2015). Participants responded to a visual stimulus—a dog's or a cat's head presented in one of four horizontal screen locations—by pressing the corresponding key ('S', 'F', 'J', or 'L' from left to right) (Figure 1A). The visual stimulus signaled either a 'Go' trial, requiring a fast key press response corresponding to the location of the stimulus, or a 'No-Go' trial, instructing participants to withhold any key press. On 'Go' trials, a correct key press led to the immediate disappearance of the stimulus, followed by a 120 ms interstimulus interval before the subsequent stimulus. In contrast, an incorrect response on a 'Go' trial meant the stimulus persisted until the correct key was pressed. For 'No-Go' trials, the stimulus was displayed for a fixed duration of 1000 ms, irrespective of any input from the participant.

The stimuli (including both 'Go' and 'No-Go' trials) followed a probabilistic eight-element sequence, alternating between predictable (pattern) and unpredictable (random) elements (e.g., 2 – r – 4 – r – 3 – r – 1 – r, where 'r' denotes a random location and numbers indicate the four positions from left to right) (Figure 1B). Each participant completed the task with one of 24 repeating eight-element sequences across 30 blocks, with each block containing ten repetitions. Short breaks and thought probes followed each block.

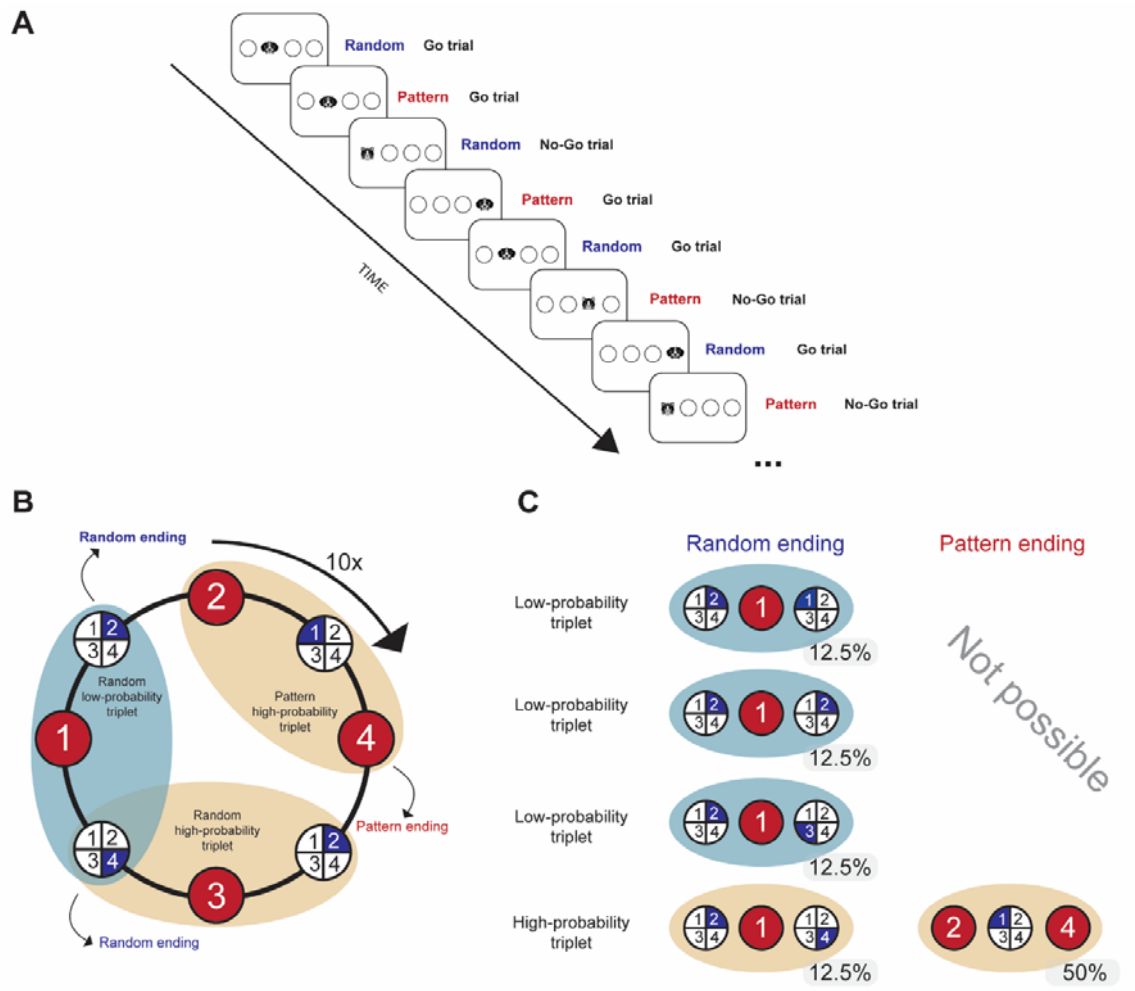

Figure 1. The Cognitive Trade-off Task. (A) Participants' primary objective was to press the key that matched the on-screen location of a target stimulus (‘Go’ trial). Occasionally, a ‘No-Go’ stimulus appeared instead of the ‘Go’ stimulus, and participants had to withhold their response to these trials (‘No-Go’ trial). A key feature of this task was the underlying structure of the stimulus presentation: every second trial was part of an 8-element probabilistic sequence. The ‘No-Go’ stimuli could be either a pattern or a random element. Participants completed 80 trials in a block, of which 10 were ‘No-Go’ stimuli. **(B)** Participants encountered sequences of three consecutive trials, referred to as "triplets". Elements could be either a pattern (red background) or random elements (blue background). Pattern elements consistently appeared in the same position throughout the task. In contrast, random elements were randomly chosen from four possible positions for each occurrence. The design of the task led to a probabilistic sequence structure, resulting in certain triplets appearing more frequently (high-probability triplets) than others (low-probability triplets). **(C)** The formation of high-probability triplets primarily involved two main configurations. In 50% of the trials, the triplet consisted of two pattern trials and one random trial positioned in the center. Another configuration, occurring in 12.5% of trials, involved two random trials and one pattern trial at the center, also forming a high-probability triplet. Combined, these configurations meant that 62.5% of all trials concluded with a high-probability triplet, while the remaining 37.5% were the final elements of a low-probability triplet.

The CTT employed a probabilistic sequence structure where certain three-element sequences (triplets) occurred with higher probability (high-probability triplets) than others (low-probability triplets). A single presentation within the sequence, whether pattern or random, constituted a trial and, critically, could also be the final element of a high- or low-probability triplet (high- vs. low-probability trials). The analysis focused on whether a trial concluded a high- or low-probability triplet, irrespective of its pattern or random designation within the alternating sequence. For instance, in the sequence 2 – r – 4 – r – 3 – r – 1 – r, triplets like 2-X-4, 4-X-3, 3-X-1, and 1-X-2 (where X is the middle element) were high-probability, while triplets like 2-X-1 or 2-X-3 were low-probability (Figure 1B; note that Figure 1B illustrates three example triplets: a pattern-ending high-probability triplet [2(P)-1(R)-4(P)], a random-ending high-probability triplet [2(R)-3(P)-4(R)], and a random-ending low-probability triplet [4(R)-1(P)-2(R)]; however, every three consecutive elements formed either a high- or low-probability triplet. For example, within the sequence 2(P)-1(R)-4(P)-2(R)-3(P)-4(R)-1(P)-2(R), six triplets are formed starting with the first pattern element: 2(P)-1(R)-4(P), 1(R)-4(P)-2(R), 4(P)-2(R)-3(P), 2(R)-3(P)-4(R), 3(P)-4(R)-1(P) [all high-probability], and 4(R)-1(P)-2(R) [low-probability]. Subsequent references to triplet type will focus on trials serving as the final element of these high- or low-probability triplets).

Across the task, 64 distinct triplets were possible (16 high-probability, 48 low-probability). High-probability triplets comprised either two pattern trials with a central random trial (50% occurrence) or two random trials with a central pattern trial (12.5% occurrence) (Figure 1C). Overall, 62.5% of trials were the final element of a high-probability triplet (high-probability trials), and 37.5% were the final element of a low-probability triplet (low-probability trials).

Each block of the CTT consisted of 70 ‘Go’ trials and 10 ‘No-Go’ trials. We randomly assigned the position of the ‘No-Go’ trials in each block, ensuring an equal distribution between random and pattern trials. Additionally, we ensured that two ‘No-Go’ stimuli never appeared consecutively, and a ‘No-Go’ stimulus was never among the first two trials. ‘Go’ and ‘No-Go’ trials were distinguished by different visual stimuli: a dog's head or a cat's head. The mapping of dog and cat heads to the ‘Go’ trial condition was counterbalanced across all participants and, specifically, balanced between those who reported a preference for dogs versus cats to control for potential preference-related biases.

Thought probes

After each block of the CTT, we asked participants to report on their mental state. While our primary goal was to investigate if MW, defined as task-unrelated thought, was associated with response inhibition and implicit statistical learning, we also explored three specific aspects: MW episodes with reportable content in contrast to "mind blanking" (MB, off-task periods with no reportable mental content), spontaneous versus deliberate manifestations of MW, as well as MW with positive vs. negative emotional content.

To achieve this, participants answered four questions after each block, designed to differentiate between these aspects. The first question (Q1) asked, "*To what degree were you focusing on the task just before this question?*" with responses ranging from 1 (Not at all) to 4 (Completely). A score of 1 indicated their thoughts were completely elsewhere (e.g., friends, weekend plans), while a 4 meant they were entirely focused on the task.

If the answer to Q1 was either 1 or 2 (indicating a MW state), the following second question (Q2) appeared: "*To the degree to which you were not focusing on the task, were you thinking of something in particular or just thinking about nothing?*" (1 - I was thinking about nothing; 4 - I was thinking about something in particular). A score of 1 meant their mind had wandered, but they were not thinking of anything specific, whereas a 4 meant they were thinking about something concrete (e.g., a book, recent events, task difficulty, or hunger). The third question (Q3) asked, "*Were you deliberate about where you focused your attention, or did it happen spontaneously?*" (1 - I was completely spontaneous; 4 - I was completely deliberate). A score of 1 suggested their attentional focus was effortless, while a 4 indicated they consciously directed their attention. The fourth question (Q4) asked, "*Were your thoughts more positive or more negative?*" (1 - Completely positive; 4 - Completely negative). A score of 1 indicated the thoughts were completely positive, while a 4 indicated their thoughts were completely negative.

If the answer to Q1 was either 3 or 4 (indicating an off-task state), instead of the three questions about the features of MW, control questions were posed ("*Did you focus more on speed or accuracy in the previous block?*", "*How difficult was it for you to concentrate on the task in the previous block?*" and "*How tiring did you find the task?*").

We opted for these four questions instead of a single, complex thought probe to avoid overwhelming participants and to gain a more nuanced understanding of their mental states.

Participants selected their response by pressing a key from 1 to 4 on their keyboard. Results related to Q2-Q4 can be found in the Supplementary Material in sections S3, S4, and S5.

Procedure

The experiment was executed via the Gorilla platform for online experimentation (https://gorilla.sc). Participants first provided informed consent, followed by a detailed explanation on the interpretation of the MW probes and the evaluation of their mental attention in various contexts (identical as described in Vékony et al., 2025). Participants thereafter undertook a concise quiz to evaluate their understanding and received the assessment. Following the quiz, participants completed 30 blocks of the CTT. After each block, participants responded to the thought probes and received feedback on their average reaction time (RT) and accuracy. After the task, participants were asked if they noticed any patterns and to describe them if they did. None of the participants could accurately define the alternating pattern integrated into the task. Participants then provided demographic information (e.g., age, gender, education) as well as responded to questions about their consumption and conditions to elucidate their observations.

Statistical learning and visuomotor performance scores

For the CTT, each 'Go' trial was categorized as the final element of either a high- or low-probability triplet based on the two preceding trials. To ensure robust analysis, trills (e.g., 1-2-1) and repetitions (e.g., 2-2-2) were removed to minimize the impact of pre-existing response tendencies (Song et al., 2007); the first two trials of each block were also excluded as they could not form a complete triplet; and trials with reaction times falling outside ±3 times the individual median absolute deviations, or those below 100 ms or above 1000 ms, were similarly discarded. Following the removal of outliers, the RT data remained marginally right-skewed; thus, square-root transformation was applied to enhance normality.

We defined two key types of learning: *statistical learning*, operationalized as the difference in RT between high-probability and low-probability trials (referred to as the statistical learning score), and *visuomotor performance*, which encompassed the overall reaction time on the task and how these changed over time, irrespective of item probability.

No-Go performance score

We calculated the percentage of correct 'No-Go' trials in each block to evaluate inhibitory control performance. A response was categorized as correct if no response key was pressed during the 1000-ms-long presentation of the 'No-Go' stimulus.

MW scores

A dichotomous MW variable was created by categorizing the responses to thought probe Q1 into MW (off-task) (1–2) and on-task (3–4) periods. Contrasts between MW with identifiable content vs. MB were created by dichotomizing responses to Q2 (1–2 vs. 3–4). Similarly, we contrasted task performance between spontaneous vs. deliberate MW by categorizing responses to Q3 (1–2 vs. 3–4) and between positive vs. negative MW by categorizing responses to Q4 (1-2 vs. 3-4) for thought probes indicating MW for Q1.

Statistical analysis

Statistical analysis was conducted in *R* (4.2.3). Simple regressions utilized the *lm* function from the *lme4* package, while linear mixed models (LMMs) were fitted using the *mixed* function (from *afex*) with sum-to-zero contrasts. For LMMs, we began with a maximal random-effects structure and simplified it to achieve convergence by removing correlations between random slopes or the slopes themselves (Meteyard & Davies, 2020). Numerical fixed factors were mean-centered. Estimated marginal means and estimated marginal trends for post-hoc simple means and simple slopes analyses were calculated with the *emmeans* package. Fixed effects were evaluated using Type III tests, and significant interactions with continuous predictors were examined at ±1 SD of No-Go performance or at the initial, mean, and final values of the Block variable (referred to as timepoints). All analyses used an alpha level of .05. Figures were generated with *ggplot2*, supplemented by *sjPlot*, *cowplot*, *ggplot*, and *afex* packages.

We conducted simple regressions to examine the evolution of MW during learning. Our outcome variables were mean MW scores and the proportion of participants engaged in MW (MW vs. on-task periods), with Block (1-30) as factors.

We performed a linear mixed model (LMM) to evaluate MW's impact on response inhibition. The outcome variables were accuracy on 'No-Go' trials (in percentage), calculated per

participant for each block. Fixed effects in this LMM included Block (1–30), MW (MW vs. on-task periods), and their interactions.

To understand the impact of MW on statistical learning and visuomotor performance, we also investigated with LMMs. The outcome variables were mean RT on ’Go’ trials, calculated per participant for each block. To differentiate the assessment of statistical learning from response inhibition, the analysis of statistical learning on ‘Go’ trials primarily focused on RT (see analysis on accuracy in S2 section of the Supplementary Materials). This approach helped to avoid confounding measures, given that accuracy on ‘No-Go’ trials was specifically used to evaluate inhibitory control. First, we ran a model with fixed effects including Block (1–30), Triplet Type (last element of high- vs. low-probability triplets) and their interactions. Next, we ran another model including also MW (MW vs. on-task periods) and its interactions. We performed a more complex model by adding response inhibition performance as a continuous variable to the model (the percentage of correct ‘No-Go’ responses) along with their interactions. Model comparisons were performed using the *anova*() function and comparing the Akaike Information Criterion (AIC) values. Please note that Triplet Type main effects and interactions signal differences in *statistical learning*, while main effects and interactions without Triplet Type reflect differences in *visuomotor performance*.

Fulll model tables can be found in the S1 section of the Supplementary Materials.

Results

MW increases with task progression

A simple linear regression revealed a relationship between the progression of the task (Block 1–30) and participants' mean MW scores. The model was statistically significant, $F(1, 7188) = 507.5$, $p < .001$, explaining a significant portion of the variance in MW scores (adjusted $R^2 = .065$). Specifically, task Block was a significant negative predictor of MW scores, $b = -0.028$, $t(7188) = -22.53$, $p < .001$. This result indicates that as participants progressed through the task, their scores tended to decrease (indicating more MW) (Figure 2A).

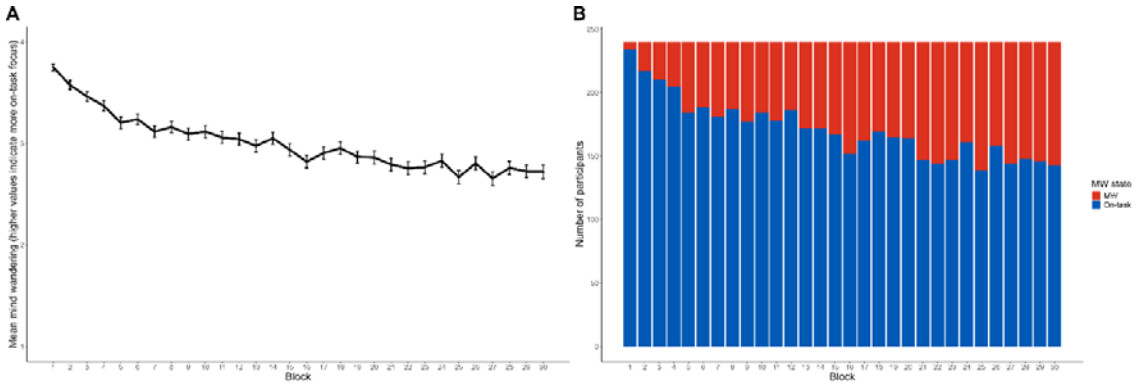

Figure 2. Change in MW throughout the CTT. (A) Mean MW score per block, as reported by participants. The x-axis represents block number, and the y-axis shows the average MW score (on a scale of 1–4, where lower scores indicate more MW). Error bars indicate SEM. (B) Number of participants engaged in MW per block. The x-axis indicates block number, while the y-axis reflects the number of participants. Stacked bars differentiate between participants who reported MW (red) and those who reported on-task focus (blue).

A simple linear regression was performed to examine the relationship between task Block (1–30) and the proportion of participants engaged in MW (0–100%). The analysis revealed a statistically significant relationship, $F(1, 28) = 140.4$, $p < .001$. The model accounted for a substantial amount of the variance in MW engagement, with an adjusted R^2 of .83. The regression coefficient for Block ($b = 0.010$, $t(28) = 11.849$, $p < .001$) indicated a positive relationship: as the task progressed, the proportion of participants engaged in MW increased (Figure 2B).

MW impairs response inhibition

An LMM was conducted to examine the effects of MW on response inhibition (defined as 'No-Go' accuracy), incorporating a by-participant random slope for Block (1-30), MW (MW vs. on-task), and their interaction to account for individual variability. The analysis revealed significant main effects for both MW ($F(1, 183.93) = 144.37$, $p < .001$) and Block ($F(1, 212.98) = 152.18$, $p < .001$), indicating that response inhibition significantly differed across levels of both factors. More specifically, response inhibition was worse during MW periods ($b = -0.046$, $SE = 0.004$) and significantly decreased as the task progressed ($b = -0.053$, $SE = 0.004$) (Figure 3). However, the interaction between MW and Block was not statistically significant ($F(1, 155.74) = 0.140$, $p = .712$), suggesting that the effect of MW on response inhibition did not change with the progress of the task.

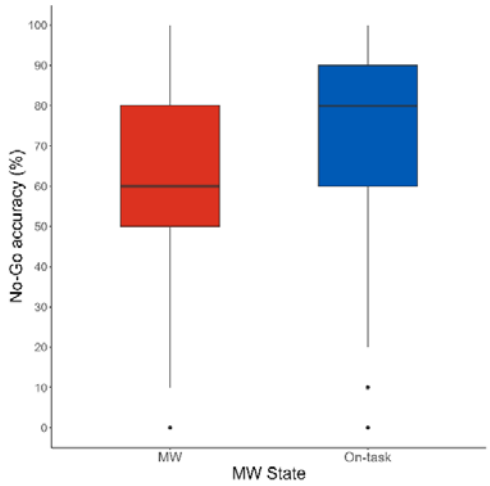

Figure 3. No-Go accuracy in the CTT. The x-axis represents the MW state reported by participants (MW or on-task), and the y-axis shows the mean accuracy on the 'No-Go' trials. During periods of on-task states, participants performed significantly better on the 'No-Go' trials, i.e., they were more successful in inhibiting the keypresses. Whiskers denote 1.5 times the interquartile range, while outliers beyond this range are depicted as dots.

Statistical learning is observed in the CTT

A LMM was conducted to evaluate whether statistical learning occurred in the CTT. Block (1-30) and Triplet Type (the last element of a high- vs. low-probability triplet) were fixed effects in the model. The dependent variable was RT on 'Go' trials.

The model converged with by-participant correlated random slopes for the Block and Triplet Type factors. The main effect of Block was significant ($F(1, 236.67) = 216.45$, $p < .001$), suggesting faster RTs as the task progressed ($b = -0.413$, $SE = 0.08$).

The main effect of Triplet Type ($F(1, 228.16) = 103.18$, $p < .001$) indicated overall faster RTs for the last element of high-probability triplets ($b = -0.078$, $SE = 0.028$), signaling statistical learning. The interaction between Block and Triplet Type was also significant ($F(1, 13624.51) = 14.50$, $p < .001$). The post-hoc comparison of estimated marginal means demonstrated a progressively enhancing difference between high- and low-probability trials (1st timepoint: $b = -0.101$, $SE = 0.021$, $p < .001$; 2nd timepoint: $b = -0.156$, $SE = 0.015$, $p < .001$; 3rd timepoint: $b = -0.211$, $SE = 0.021$, $p < .001$), signifying that statistical learning improved as the task advanced.

Statistical learning is affected by MW

As we observed that statistical learning did occur in the CTT, we examined how MW (MW vs. on-task) periods interacted with statistical learning. An LMM was conducted with MW (MW vs. on-task) as an additional fixed effect in the model. The dependent variable was RT on 'Go' trials.

The model converged with by-participant correlated random slopes for the Block and MW factors and their interaction. The AIC comparison of the models with (*AIC* = 37494) and without the MW factor (*AIC* = 37864) indicated better goodness of fit for the more complex model ($\chi 2(8) = 385.93$, $p < .001$). Triplet Type and Block main effects, as well as their interaction, appeared similarly as in the simpler model (see Supplementary Material S1.3 for details).

A main effect of MW appeared ($F(1, 115.65) = 17.11$, $p < .001$), indicating faster RTs during periods of MW ($b = -0.076$, $SE = 0.018$). The interaction between MW and Block was also significant ($F(1, 140.84) = 8.59$, $p = .004$). The post-hoc comparison of estimated marginal means revealed a progressively decreasing difference between MW and on-task periods in RT (1st timepoint: $b = -0.244$, $SE = 0.043$, $p < .001$; 2nd timepoint: $b = -0.152$, $SE = 0.037$, $p < .001$; 3rd timepoint: $b = -0.060$, $SE = 0.054$, $p < .001$), indicating that the effect of MW on general RTs was stronger in the beginning of the task.

Most significantly, the interaction between Triplet Type and MW was also significant ($F(1, 13326.22) = 6.05$, $p = .014$), suggesting that the magnitudes of statistical learning between MW and on-task periods differed. Analysis of post-hoc estimated marginal means revealed a larger RT difference between high- and low-probability trials during periods of MW ($b = -0.206$, $SE = 0.027$) than during on-task periods ($b = -0.128$, $SE = 0.017$) (Figure 4). No additional interactions concerning the MW factor were significant ($p > .170$).

To sum up, when participants experienced MW, their visuomotor performance was associated with faster responses. Simultaneously, their RTs indicated improved statistical learning, meaning they were better at differentiating between less and more predictable elements.

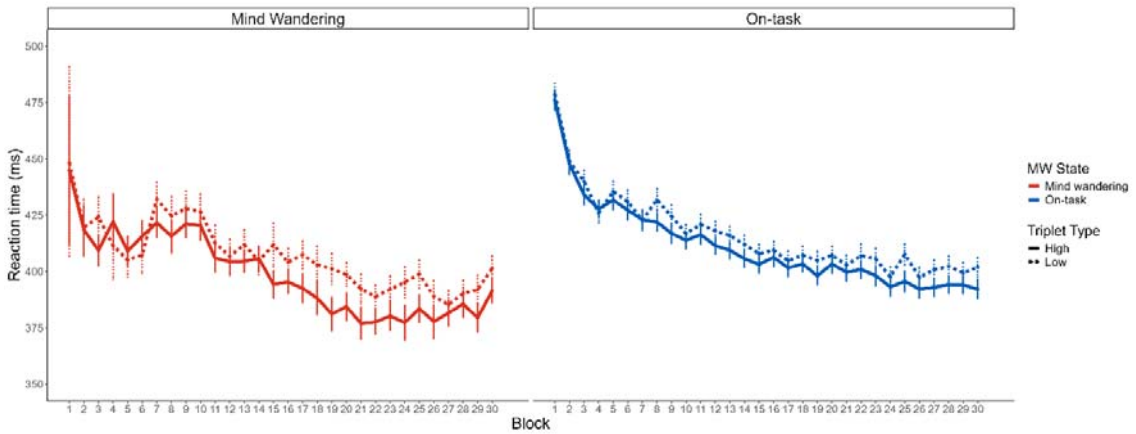

Figure 4. Statistical learning in RT and MW. The x-axis displays the blocks of the ASRT task, with the y-axis showing raw RTs in milliseconds. Whereas dashed lines indicate RTs to low-probability triplets, solid lines indicate RTs to high-probability triplets. Please note that the gap between the dashed and solid lines indicates statistical learning performance. Red indicates periods of MW, and blue signifies an on-task state. Error bars illustrate the standard error of the mean (SEM). Overall, statistical learning was enhanced (i.e., a bigger gap is observed between the dashed and solid lines) during periods of MW.

Response inhibition modulates the relationship between MW and statistical learning

Given our finding of improved statistical learning during periods of MW, our next objective was to investigate whether response inhibition modulates this relationship. We ran an LMM that included the No-Go Performance (percentage of correct 'No-Go' responses) as a continuous fixed effect. The dependent variable was RT on 'Go' trials.

The model achieved final convergence, incorporating random slopes for Block, MW, and their interaction across participants. The AIC comparison of the models without (*AIC* = 37494) and with the No-Go performance fixed effect (*AIC* = 36497) indicated better model fit for the more complex model ($\chi 2(8) = 1012.84$, $p < .001$). Main effects for Triplet Type and Block, as well as the interaction between MW and Block remained significant (see full results in Supplementary Material S1.4). The main effect of No-Go performance was also significant ($F(1, 10669.10) = 841.54$, $p < .001$), indicating faster RT in blocks of worse No-Go performance ($b = 1.44$, $SE = .049$). The interaction between No-Go Performance and Block was also significant ($F(1, 9740.16) = 4.61$, $p = .032$). We calculated values at the beginning, the middle point, and the end point of the Block factor and performed simple slopes analysis, which revealed no difference between timepoints in the slopes of No-Go performance (all $p > .08$). A MW by No-Go Performance interaction appeared ($F(1, 9045.37) = 12.13$, $p < .001$),

indicating that the effect of MW on visuomotor performance is dependent on response inhibition—participants show faster RT during MW in the case of weak No-Go performance (b = -0.117, SE = .045, p < .010) and slower RTs in the case of good No-Go performance (p < .044, b = 0.080, SE = .040). The three-way interaction between Block, No-Go accuracy, and MW was also significant (F(1, 8706.63) = 15.41, p < .001). Post-hoc comparison of estimated marginal trends indicated that the MW effect on No-Go performance was increasingly bigger as the task progressed (1st timepoint: b = -0.298, SE = 0.207, p = .151; 2nd timepoint: b = 0.323, SE = 0.099, p = .001; 3rd timepoint: b = 0.988, SE = 0.174, p < 0.001).

Concerning statistical learning performance, a significant interaction between Triplet Type and No-Go performance emerged (F(1, 13370.63) = 35.98, p < .001). Post-hoc comparison of estimated marginal means indicated progressively smaller differences between high- and low-probability triplets as the No-Go performance increased, with the biggest difference being in the case of weak No-Go performance (b = -0.326, SE = 0.034, p < .001), a smaller difference at mean No-Go performance (b = -0.170, SE = 0.017, p < .001), and no difference in the case of good No-Go performance (b = -0.015, SE = 0.027, p = .581). The three-way interaction between Triplet Type, No-Go performance, and Block was also significant (F(1, 13379.92) = 5.52, p = .019). Post-hoc estimated marginal means calculated for the mean and +/- 1 SD No-Go performance indicated significant change in statistical learning as the task progressed only in the case of low No-Go performance (poor No-Go performance: p = .032; medium No-Go performance: p = .389; good No-Go performance: p = .695). Importantly, a three-way interaction between Triplet Type, MW, and No-Go Performance emerged (F(1, 13386.53) = 11.22, p < .001). Estimated marginal means indicated a larger difference between RTs to high- and low-probability trials (i.e., statistical learning) during periods of MW compared to on-task periods in the case of weak No-Go performance (b = -0.224, SE = 0.068, p = .001), no difference between the two states in the case of medium No-Go performance (b = -0.050, SE = 0.033, p = .132), and slightly worse learning during MW in the case of good No-Go performance (b = 0.123, SE = 0.054, p = .023) (Figure 5).

These results indicate that the effect of MW on statistical learning depends on response inhibition, which indicates that compared to an on-task state, MW enables efficient statistical learning via suppressing executive control processes. No other interactions were significant (see full results in Supplementary Material S1.4). To sum up, response inhibition seems to modulate the relationship between MW and both visuomotor performance and statistical

learning. Specifically, when response inhibition was poorer, MW was linked to quicker visuomotor responses and better statistical learning.

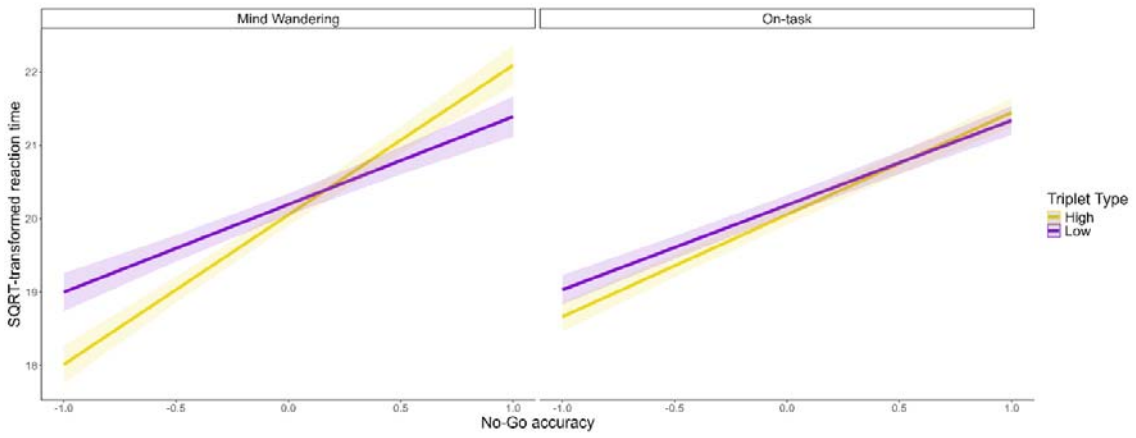

Figure 5. The effect of 'No-Go' accuracy on statistical learning in RT. The y-axis shows SQRT-transformed RT, while the x-axis represents centered 'No-Go' accuracy, with higher values representing better response inhibition. The yellow and purple lines indicate the estimated marginal means for low- and high-probability trials, respectively. Separate subplots differentiate this relationship during MW (left) and on-task periods (right). Error bars indicate SEM. Critically, during MW, statistical learning (the difference between high- and low-probability trials) is more pronounced with weaker 'No-Go' accuracy. Conversely, with stronger 'No-Go' accuracy, the opposite pattern is observed.

Discussion

This study investigated the relationship between MW, response inhibition, and statistical learning within a single experimental design. Our findings largely replicate previous research regarding the distinct effects of MW on executive control and statistical learning, while providing new insights into how these cognitive processes interact. Consistent with existing literature (Kam & Handy, 2014; Maillet et al., 2020), we observed that MW was associated with impaired response inhibition, as evidenced by decreased accuracy on 'No-Go' trials during MW periods. This result suggests that when attention drifts away from the task, individuals are less effective at suppressing prepotent responses. Simultaneously, previous studies (Simor et al., 2025; Vékony et al., 2025) have already shown that periods of MW resulted in impaired visuomotor performance and enhanced statistical learning. Crucially, however, our study revealed a significant modulation of the relationship between MW and statistical learning through response inhibition.

We found that weaker response inhibition was associated with greater statistical learning during periods of MW. This suggests a potential trade-off: when executive resources are temporarily depleted due to MW, the brain may become more attuned to implicit statistical regularities (Simor et al., 2025; Vékony et al., 2025), leading to enhanced learning in terms of speed of processing. On the other hand, robust response inhibition performance was associated with diminished statistical learning during periods of MW. This aligns with the competition framework, which posits an antagonistic relationship where statistical learning thrives when cognitive control is less engaged – but now we demonstrate that this relationship is modulated by the focus of attention (MW vs. on-task). Previous research has suggested a negative association between statistical learning performance and control functions mediated by the prefrontal cortex. For instance, studies have shown negative correlations between statistical learning and frontoparietal network activity (Tóth et al., 2017), and inhibitory non-invasive brain stimulation targeting the dorsolateral prefrontal cortex has been shown to improve predictive processing as measured by statistical learning (Ambrus et al., 2020; Szücs-Bencze et al., 2025). Our direct measurements corroborate and extend these prior indications, providing empirical evidence for this inverse relationship. The observed increase in statistical learning during MW in our study is particularly salient given that MW is inherently linked to impaired task-associated cognitive control, consistent with the executive failure view (McVay & Kane, 2010). This view posits that MW episodes arise from an inability to maintain current goals, leading to reduced sustained task focus and increased susceptibility to task-unrelated interference.

Episodes of MW have also been coupled with increased activity in the frontoparietal network, providing a neural basis for how the brain's executive system may be transiently down-regulated to facilitate the extraction of statistical regularities from the environment (Christoff et al., 2016; Smallwood et al., 2012). Our direct behavioral measures of executive functions during MW similarly revealed a decrease in executive performance, directly supporting the notion of executive failure during these periods. This direct evidence for compromised executive control during MW, alongside enhanced statistical learning, provides compelling support for a modulatory role of executive functions in statistical learning. Our direct measurement approach provides a robust foundation for such investigations into the nuanced interplay between these fundamental cognitive processes.

We speculate that during offline moments such as MW, the brain replays previously encountered sequences and engages in internal simulations of potential sequence variations and transitions. This generative process may allow the brain to explore alternative combinations of events beyond those explicitly experienced, effectively filling in gaps and refining its internal model of the underlying structure. Such simulations likely support the abstraction of statistical regularities by amplifying co-occurrence patterns and reinforcing predictive associations, even in the absence of direct sensory input. In this way, transient offline states such as MW may serve as a window for unsupervised internal modeling, contributing to more efficient statistical learning. Our findings, together with previous research (Simor et al., 2025; Vékony et al., 2025), raise the possibility that this process may be driven by memory consolidation associated with local sleep occurring in the waking brain (Wamsley, 2022; Wamsley & Summer, 2020). Statistical learning was most pronounced when inhibitory control was at its lowest, aligning with theories suggesting that local-sleep-like neural states may enhance model-free learning by attenuating frontoparietal executive networks. This interpretation is consistent with the idea that local-sleep-dependent consolidation stabilizes recent memories and supports the formation of predictive models of environmental regularities (Vékony et al., 2025). However, more studies using methods like magnetoencephalography or intracranial electroencephalography are needed to explore the link between MW, local sleep activity, and how we develop predictive models.

Human cognition must balance the demands of goal-directed focus with the need to learn from the environment. Here, we dissect this balance and reveal a key mechanism governing the interplay between internal thoughts and statistical learning. We demonstrate that the enhancement of statistical learning during MW is directly modulated by the efficacy of response inhibition. While we confirmed previous findings that MW diminishes inhibitory control and accelerates responses to predictable patterns, our significant advancement is demonstrating that these effects are not parallel. The magnitude of the learning benefit during MW is reliant on the inadequacy of inhibitory control, providing direct evidence for this functional trade-off and suggesting that executive dysfunction facilitates implicit learning. This inverse relationship offers support for neurocompetition models that posit an antagonistic relationship between executive and implicit statistical learning systems. These results reframe the adaptive function of MW, suggesting that it may represent a cognitive state optimized not for immediate goal pursuit but for the continuous, unsupervised acquisition of a predictive model. This dynamic interplay between internally- and externally-

directed cognitive modes appears to be a fundamental mechanism that allows for flexible adaptation in a complex and ever-changing environment.

Acknowledgement

This work was supported by the Chaire de Professeur Junior Program by Inserm and the French National Grant Agency (ANR-22-CPJ1-0042-01); the National Brain Research Program project NAP2022-I-2/2022 (D.N.) of the Hungarian Academy of Sciences; the Hungarian National Research, Development and Innovation Office grant NKFI FK 142945 (P.S.) and 128016 (D.N.); and the Janos Bolyai scholarship of the Hungarian Academy of Sciences (P.S.).

Author contributions

Conceptualization: T.V., G.C., P.S., and D.N.; methodology: T.V., B.B., G.C., P.S., and D.N.; software: T.V.; validation: T.V., G.C., P.S., and D.N.; formal analysis: T.V. and B.B.; investigation: T.V. and D.N.; resources: T.V., B.B., G.C., P.S., and D.N.; data curation: T.V.; writing—original draft: T.V., G.C., P.S., and D.N.; writing—review and editing: T.V., B.B., G.C., P.S., and D.N.; visualization: T.V.; supervision: G.C., P.S., and D.N.; project administration: T.V., G.C., P.S., and D.N.; funding acquisition: P.S. and D.N.

Declaration of interests

The authors declare no competing interests.

Data availability statement

The raw data and all codes required to duplicate the results, figures, and tables are accessible at the following OSF repository:

https://osf.io/53jqs/?view_only=37ef7f12c7c3416fbf9992b6c4109624

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