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Too Alert to Think Straight: Combined Neurophysiological and Modeling Evidence of Impaired Internal Shielding During Hypervigilance

Nan Wang¹  | Sam Verschooren^{2,3}  | Gilles Pourtois¹ 

¹Cognitive and Affective Psychophysiology Laboratory, Department of Experimental Clinical and Health Psychology, Ghent University, Ghent, Belgium | ²Institute for Psychology, Arctic University of Norway, Tromsø, Norway | ³Department of Neurology, Max Planck Institute for Human Cognitive and Brain Sciences, Leipzig, Germany

Correspondence: Nan Wang (nan.wang@ugent.be)

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ABSTRACT

Hypervigilance usually refers to the enhancement of external attention in an effort to scan and detect potential threats in the environment. Yet, whether this affective state could also influence internal attention or the ability to switch between external and internal attention (i.e., attentional balance) remains unclear. Recent studies have shown that attentional balance is characterized by internal dominance, raising the intriguing possibility that hypervigilance might alter attentional balance rather than merely boosting external attention. To test this hypothesis, we recorded behavioral, EEG, and eye-tracking data from 46 participants performing the Switching Attention Task (SAT) under hypervigilance versus two other control conditions. The SAT has previously been validated to explore attentional balance. Hypervigilance was induced during the SAT through a task-unrelated aversive sound played unpredictably, and its induction was confirmed by skin conductance, subjective ratings, and eye fixation data. At the behavioral level, using a drift diffusion model, we found that hypervigilance impaired attentional balance during the SAT, by decreasing the shielding of internal attention. Interestingly, we found that this impairment was captured by an amplitude modulation of the P2 event-related potential. A joint modeling approach further confirmed this specific brain-behavior association. Together, these findings suggest that hypervigilance modulates attentional balance through a selective modulation of internal attention.

1 | Introduction

Daily life requires individuals to flexibly navigate between sensory information from the external environment and internally generated representations from memory (Weber et al. 1986). Attentional control, therefore, relies on the ability to switch attention within and between these two domains depending on task demands or contextual factors (Chun et al. 2011; Nobre and Gresch 2025; Servais et al. 2023; van Ede et al. 2025). As a result of this flexibility, attentional balance can be achieved, allowing individuals to allocate attentional resources efficiently either

externally or internally (Narhi-Martinez et al. 2023; Nobre and Gresch 2025).

Recently, there has been a surge of interest in attentional balance (e.g., Calzolari et al. 2022; Cleary et al. 2025; Gresch et al. 2024a, 2024b; Hautekiet et al. 2023; Nobre and Gresch 2025; Poskanzer and Aly 2023; Servais et al. 2023; Treder et al. 2021; Verschooren, Liefoghe, et al. 2019a; Verschooren, Schindler, et al. 2019b; Verschooren et al. 2020, 2021, 2025). To investigate this experimentally, the Switching Attention Task was developed (SAT; see Verschooren,

Schindler, et al. 2019b; Verschooren, Liefoghe, et al. 2019a). In this task, participants are cued on a trial-by-trial basis to process either external visual stimuli or stimuli retrieved from visual memory (encoded in a separate phase before the main experimental session). These two trial types are presented in a random order, in turn creating either repetitions or switches of external and internal attention (Verschooren et al. 2020, 2025; Verschooren, Liefoghe, et al. 2019a). A consistent behavioral finding using the SAT is that switching between external and internal attention incurs a switch cost, typically reflected in longer reaction times (RTs), on switch trials relative to repeat trials (e.g., Verschooren, Schindler, et al. 2019b; also see Gresch et al. 2021). Importantly, this switch cost is asymmetrical: it is larger when switching from external to internal attention than when switching from internal to external attention (Hautekiet et al. 2023; Verschooren et al. 2020, 2021; Verschooren et al. 2025; Verschooren, Liefoghe, et al. 2019a; also see Gresch et al. 2024b for a similar finding with a different task). Building on these findings, it has been proposed that this asymmetry reflects an internal shielding benefit (Verschooren et al. 2020, 2025; Verschooren and Egnér 2023). Specifically, during internal attention, the content of the focus of attention can be shielded more effectively from interference than during external attention. Crucially, this difference in shielding efficiency is most evident on repetition trials, when participants repeatedly engage the same attentional domain (Verschooren et al. 2020, 2025). On switch trials, however, interference occurs for both external and internal attention, as a working memory update needs to take place to reset the attentional set (Verschooren et al. 2020, 2021). As a result of the enhanced shielding on internal repetition trials specifically, a greater difference between repeating internal attention and switching to it is observed in RTs, compared to external attention (Dreisbach and Haider 2008, 2009; Dreisbach and Wenke 2011). Eventually, this leads to a larger switch cost for internal compared to external attention, as both repetition and switching are susceptible to interference from previously learned information during external trials (Verschooren et al. 2020).

Notably, even though attentional balance is characterized by this internal shielding benefit (which might even be a default state or mode and foster specific phenomena, such as mind wandering; Mittner et al. 2016; Raichle 2015; Smallwood and Schooler 2006, 2015), it can, however, be modulated depending on contextual demands and the specific weights assigned either to external or internal attention. Presumably, this process is context-dependent (e.g., Duncan et al. 2012; Tarder-Stoll et al. 2020; Tulving 1983). Consistent with this view, we recently demonstrated that biasing attention toward the external environment disrupts attentional balance and impairs internal shielding, giving more weight to signals from the external environment (Wang et al. 2025). We confirmed this effect at the behavioral level using the SAT by examining performance under hypervigilance, a state characterized by heightened perceptual sensitivity to environmental stimuli in an effort to detect potential threats (APA 2013; Zeigler-Hill and Shackelford 2020). In other words, hypervigilance was used as a manipulation to bias attention externally. Hypervigilance was induced by presenting a task-unrelated threatening sound unpredictably during the SAT, following standard experimental practice (Carsten et al. 2023; Grillon 2008; Grillon and

Ameli 1998; Rossi and Pourtois 2014). As control conditions, either a neutral sound was presented (neutral condition) or no sound was added (control condition). Behaviorally, we found that the asymmetry in switch costs (RTs) was present in both the control and neutral conditions but disappeared under hypervigilance. Moreover, to further explore the underlying cognitive mechanism, we used a drift diffusion model (DDM) to analyze these behavioral data (Ratcliff and Rouder 1998; Wiecki et al. 2013), and we found that drift rate (v) captured the switch cost asymmetry in the control and neutral conditions, whereas this asymmetry was absent under hypervigilance. Critically, this change was driven by a selective reduction in drift rate on internal repetition trials. Previous DDM studies have shown that drift rate can index interference control processes during the switching process (Schmitz and Voss 2012, 2014). In the context of attentional balance, we therefore interpret drift rate as reflecting shielding efficiency. Given that the internal shielding benefit is primarily expressed on internal repetition trials (see above), the observed reduction in drift rate suggests a specific impairment in internal shielding under hypervigilance (Wang et al. 2025).

However, the specific brain mechanisms through which hypervigilance influences attentional balance (internal shielding in particular) remain unclear. Although our previous behavioral findings did not indicate a facilitation of external attention, prior research on hypervigilance has shown that this affective state can enhance early sensory processing, independent of stimulus valence. Specifically, hypervigilance has been associated with increased amplitudes of early visual evoked components, such as the C1 (approximately 24–40 ms) and the P1 (approximately 80–132 ms), reflecting facilitated perceptual processing at early sensory stages (Michalowski et al. 2009; Schomberg et al. 2016; Weymar et al. 2014). Accordingly, the reduced internal shielding efficiency observed under hypervigilance in our previous study (Wang et al. 2025) may originate from alterations at early stages of sensory processing. Such early perceptual modulations could bias attentional weighting toward externally driven information, thereby weakening the ability to maintain internally focused attention. Importantly, these early sensory effects may not be detectable using behavioral measures or through DDM alone.

Interestingly, a recent electroencephalography (EEG) study using the SAT investigated attentional balance by examining target-locked visual event-related potentials (ERPs), specifically the P1, N1, and P2 components (Verschooren et al. 2025). The authors found that both the P1 and N1 components were reduced for internal compared to external trials, reflecting decreased early visual processing for the former ones. This result suggests that perceptual decoupling (i.e., disengagement from external sensory processing) appears during internal attention at an early stage following stimulus onset in the visual cortex (Korda et al. 2024; Servais et al. 2023; Smallwood and Schooler 2006). Importantly, the same study further showed that the later P2 component varied as a function of the asymmetric switch cost. Specifically, P2 amplitude was reduced for internal repetition trials relative to internal switch trials, whereas no such difference was observed for external trials. According to Verschooren et al. 2025, this modulation of the P2 may reflect a later stage of perceptual decoupling, beyond the earlier P1 and N1 effects,

and may specifically index the internal shielding benefit. This interpretation is consistent with the observation that perceptual decoupling is strongest during internal repetition trials, when internal attention can be maintained most effectively.

Taken together, these findings suggest that the behavioral modulation of attentional balance observed under hypervigilance in our previous study may originate at early stages of sensory processing, as reflected in target-locked P1 and N1 components. Specifically, hypervigilance may either enhance P1 and N1 amplitudes for external trials or attenuate the reduction of these components for internal trials. Furthermore, given the proposed role of the P2 in indexing the internal shielding benefit, hypervigilance would also be expected to modulate this ERP component, potentially mirroring the disappearance of the behavioral switch cost asymmetry observed under hypervigilance.

1.1 | The Current Study

To gain insight into the brain mechanisms underlying the modulation of attentional balance by hypervigilance, and capitalizing on these previous studies (Wang et al. 2025; Verschooren et al. 2025), we conducted a high-density EEG study in which 46 participants performed the SAT. Using a combination of EEG and DDM, we directly compared their performance during the SAT when hypervigilance was induced to two control conditions (i.e., either no sound played or a safe sound played during this task), in keeping with our previous study and experimental design (Wang et al. 2025). To confirm that hypervigilance was induced successfully, both subjective state measures and physiological arousal (using skin conductance responses, SCR) were used. In addition, given that previous work has consistently reported distinct eye-movement patterns during internal versus external attention, eye-tracking was used to examine whether fixation behavior also differed between external and internal trials during the SAT (Benedek et al. 2017; Ceh et al. 2020, 2021; Korda et al. 2024). Our primary aim was to replicate our DDM findings and to examine how target-locked ERP components associated with attentional balance, particularly the P1, N1, and P2, are modulated under hypervigilance (see above). To obtain a mechanistic understanding of how hypervigilance alters attentional balance, we further tested whether the variability in these ERP components, and especially the P2 (see Verschooren et al. 2025), could predict the main DDM parameter under consideration, namely the drift rate (Bridwell et al. 2018). To this end, we employed a joint modeling approach in which behavioral performance was predicted from trial-by-trial ERP amplitudes using single-trial regression analyses (Frank et al. 2015; Nunez et al. 2024; Turner et al. 2015, 2017). Because the drift rate (v) has been shown to represent interference control especially under the context of task switching, and in our case, to capture the efficiency of shielding one attentional type from the interference created by the other one (Karayanidis et al. 2009; Schmitz and Voss 2012, 2014; Wang et al. 2025), we mostly focused on it as main behavioral index (and specific model parameter). Specifically, we reasoned that if the P2 component reflects the internal shielding benefit, then its amplitude should predict drift rate (v) on a trial-by-trial basis (Nunez

et al. 2024). Moreover, we hypothesized that this brain-behavior association would be altered under hypervigilance.

2 | Method

2.1 | Participants

The sample size was determined based on prior work using the same SAT and a comparable experimental design (Wang et al. 2025, $n = 45$, based on a Bayesian sequential analysis), to ensure comparability of the model-based estimates. In total, we recruited 51 participants from the Belgian student community (data collected in 2024), and the data of 4 of them, who scored below 60% in at least one of the experimental conditions, were removed. The final sample comprised 46 participants (33 females), aged 18–30 years ($M = 24$, $SD = 3.01$), and 2 of them were left-handed. To provide information regarding the sensitivity of the final sample, a post hoc sensitivity analysis was conducted, which indicated that with 46 participants, the study was sensitive to detecting a minimum effect size of $\eta_p^2 = 0.099$ for a $2 \times 2 \times 3$ within-subject interaction at 80% power. This range is comparable to effect sizes observed in prior SAT work ($\eta_p^2 = 0.076$, Wang et al. 2025). Participants all had normal or corrected-to-normal vision and declared no history of psychiatric or neurological disorders, nor the use of psychoactive medication. They signed an informed consent before the start of the experiment and received €20 for their participation. The study protocol was approved by the local ethics committee (#2022–097).

2.2 | Apparatus

Participants were tested individually in an electrically shielded and soundproof room. The experiment was programmed with PsychoPy (version 2022.2.4, Peirce et al. 2019) and was presented on a CRT monitor (40.5 cm $\times$ 30 cm). Participants completed the experiment at a distance of 71 cm with their heads restrained by a chin rest, wearing insert earphones (3M E-A-RTONE-3 A, 10 Ω) through which a specific sound could be played. Participants performed the task using their dominant hand, and responses were recorded using a standard computer keyboard. Eye movements were monitored monocularly¹ using an SR Research EyeLink 1000 Plus system (SR Research Ltd 2013) at a sampling rate of 1000 Hz. The EyeLink 1000 Plus system incorporates a unique online parsing system that uses velocity and acceleration-based saccade detection methods (saccade-picking) to identify saccades and fixations. EEG data were recorded continuously using a 64-channel BioSemi Active Two system (electrodes were placed according to the extended international 10–20 system; BioSemi, Amsterdam, the Netherlands, <http://www.biosemi.com>). The sampling rate was 512 Hz, and the CMS-DRL electrodes were used as the online reference. Six external auxiliary electrodes were also included: four for monitoring the horizontal and vertical electrooculogram (EOG), and two others for the left and right mastoids. EOG electrodes were attached above and below the left eye and on the outer canthi of the two eyes. Skin conductance was recorded through two bipolar electrodes applied to the index and middle fingers of the non-dominant hand (Boucsein et al. 2012).

2.3 | Experimental Design and Materials

The experiment consisted of a 2 (Switch Type: repeat, switch) $\times$ 2 (Attention Type: external, internal) $\times$ 3 (Condition: control, neutral, negative) within-subject factorial design. It was divided into three sessions, corresponding to the three main conditions. Their order (Control-Negative-Neutral, Negative-Neutral-Control, and Neutral-Control-Negative) was counterbalanced across participants. The interaction between Switch Type and Attention Type was coded on each trial (i.e., repeat external, repeat internal, switch external, or switch internal, see Figure 1A). In each block, the trial order was random to get an equal number of trials per cell.

Sixteen non-verbalizable figures were selected from Endo et al. (2003). These figures were grouped into four sets, each containing four figures. For half of the participants, one set was assigned to external while the other one was assigned to internal trials, and likewise for the two remaining sets for the other half of the participants.

2.4 | Task and Procedure

The experiment began with a training phase designed to familiarize the participants with the task and allow them to memorize the figures for the internal trials. Both external and internal training phases were included to match practice with external and internal stimuli, with their order being counterbalanced across participants (Verschooren, Liefvooghe, et al. 2019a). During the external training phase, four figures were displayed on the screen, with one highlighted by a blue frame to indicate the target. After 250 ms, a fifth figure (the probe) appeared at the center of the screen, surrounded by the original four figures (see Figure 1B). Participants were required to determine whether the probe matched the target in shape, performing a two-alternative forced-choice task. The stimuli remained on screen for up to 10 s or until a response was made. Before the internal training phase, participants were first presented with four figures to memorize at a self-paced speed. During internal training trials, four scrambled figures were then shown, again with one location highlighted as the target. Based on their memory of the previously encoded figure set, participants performed the same target-probe matching task when a central probe appeared 250 ms later (see Figure 1C), again within a 10-s response window. Feedback was provided after every trial (i.e., either “Correct”, “False”, or “Too slow” if participants did not make a response within 10 s). For internal training trials, incorrect or missing responses were followed by the re-presentation of the original four figures together with “False” feedback, allowing further consolidation of the visual memory set. In contrast, for external training trials, only “False” or “Too slow” feedback was displayed after incorrect or missing responses. The training ended when participants reached a mean accuracy of 85% or higher in both training phases and completed a minimum of 18 correct trials per phase.

After completing the training phase, the participants moved to the experimental phase, which consisted of one practice block followed by nine experimental blocks. The task remained the same across the practice and experimental blocks, with the exception that no feedback was presented during the latter ones.

Each block contained 82 trials, with the first two trials serving as warm-up trials. Every trial began with a fixation cross displayed for a jittered duration of 300–500 ms, followed by a cue presented for 1000 ms. The cue, either the letter “E” (external) or “I” (internal), indicated which Attention Type this trial entailed. Then, five figures (a central probe surrounded by four figures (external)/scrambled figures (internal) with one of them being highlighted as the target) were shown simultaneously for 500 ms (see Figure 1B,C). Afterward, the four placeholders remained on the screen for an additional 1000 ms. Participants were required to perform the same target-probe matching task and respond within this 1500-ms window. The next trial started immediately after their response or after the time limit expired if no response was given (see Figure 1D). Participants responded using the keys ‘g’ and ‘h’ of the keyboard, with the response mapping (“match” or “non-match”) randomized across them.

The nine experimental blocks were divided into three sessions (control, negative, and neutral, see Figure 1E), with three consecutive blocks assigned to each of them. In the negative condition, a white noise burst (101 dB, 50 ms duration) was used to induce hypervigilance, in agreement with previous startle probe studies (Grillon 2008; Rossi and Pourtois 2014; Wang et al. 2025). In the neutral condition, a low-volume, non-threatening sine wave (46 dB, 200 ms duration) was played. The intensities and acoustic properties of both sounds were validated using an artificial ear (GRAS 43AG-S2, Ear and Cheek Simulator with Kemar Pinna). In the control condition, no sound was played. Before the first experimental block, both sounds were played three times each as examples (the order of the two sounds was random), and participants were reminded before every session if a sound would be played during it, and if true, which one. In the neutral and negative conditions, the corresponding sound was played unpredictably at random points within the block, occurring 4–6 times with a variable interval of 15–20 trials between two successive presentations. Sounds were never played during instructions.

The emotional state of the participants was measured four times during the experiment: the first time before the sound example and experimental blocks (baseline), and then once after each session. In our previous study (Wang et al. 2025), we found that this hypervigilance manipulation, during the SAT, did not merely increase state anxiety, as measured by the state version of the State-Trait Anxiety Inventory (STAI-Y1). Likewise, it did not increase the skin conductance level (SCL) either, while it did influence the SCR to the threatening sound. These null findings suggest that our affective manipulation did not simply increase state anxiety globally or tonically, but was likely more specific, probably increasing alertness or arousal instead (see Wang et al. 2025, for an extensive discussion of this issue). Accordingly, in the current study, we departed from the STAI, which has a low discriminant validity for hypervigilance (Bijsterbosch et al. 2019), and used instead both general and specific items to better capture the change at the subjective level induced by our manipulation. For assessing the general emotional state, we used a visual analog scale (VAS) ranging from 1 (felt very bad) to 100 (felt very good), and participants rated how they felt during the last session (for the baseline, we asked about their current state instead). To obtain a more specific estimate of their affective state, we also selected five items from the Mood and Anxiety Symptoms Questionnaire (MASQ, the

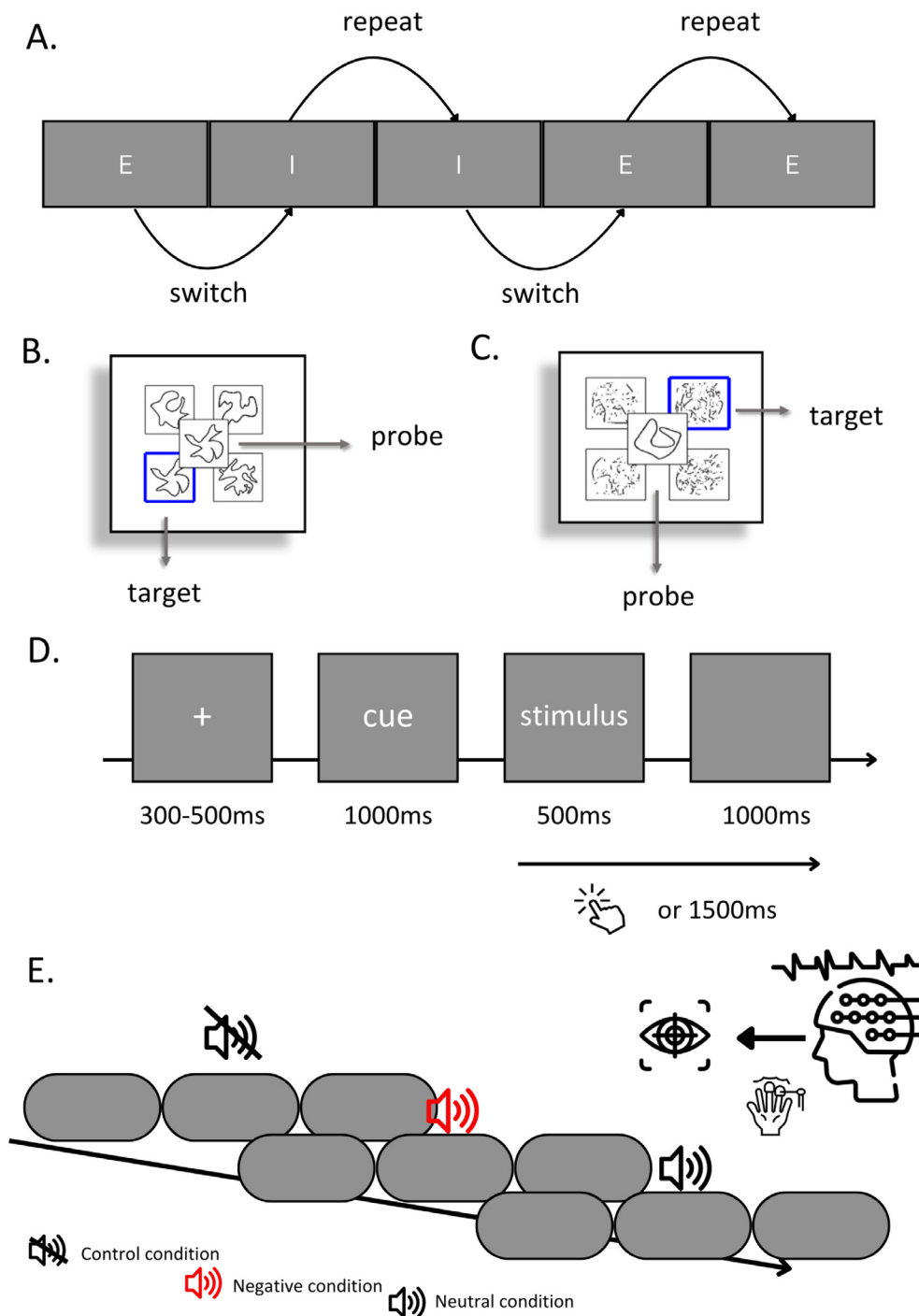


FIGURE 1 | Procedure. (A) Trial order was restricted random, enabling to create four main trial types depending on the combination of Attention Type with Switch Type: Repeat external, repeat internal, switch external, and switch internal. (B) On external trials, the matching task was based on visual stimuli shown on screen. (C) On internal trials, this task was based on visual memory instead (i.e., the four peripheral figures were encoded in memory during a separate training phase). (D) For each of them, a corresponding cue informed the participants prior to the stimulus presentation about which Attention Type to use to perform the task, either external (“E”) or internal (“I”) attention. (E) Each condition included three blocks (shown in succession), and the order of these three conditions was counterbalanced across participants. A specific sound was played several times at unpredictable intervals during the negative and neutral conditions. This sound was a white noise burst in the negative condition and a low-volume, non-threatening sine wave in the neutral condition. Skin conductance, eye fixations, and EEG were recorded continuously during these nine blocks.

90-item version, Clark and Watson 1991) and five items from the Penn State Worry Questionnaire (PSWQ, Meyer et al. 1990; Van Rijsoort et al. 1999), to measure anxious arousal (i.e., hypervigilance) and anxious apprehension (or worry), respectively (Bijsterbosch et al. 2014; Härpfer et al. 2021). Moreover, we

also added two more self-designed items to measure task concentration and sound regulation, respectively. Every time the participants needed to answer these 12 items, their order was shuffled (see Table S1 for those items and more details). In analogy with the VAS probing their general emotional state, they

needed to answer these items based on their feelings during the last session (for the baseline, they also rated their current state). Besides, the participants rated twice how much they (dis)liked the sound: once after the neutral condition and once after the negative condition. For these ratings, we also used a VAS ranging from 1 (very unpleasant) to 100 (very pleasant) and expected a lower rating for the negative than the neutral sound.

Moreover, we also measured eye fixations. Before the start of each session, the calibration of the gaze position was performed using a standard nine-point calibration procedure. As a result, there were three calibrations in total. During the nine experimental blocks, eye position, EEG, and skin conductance were recorded continuously. During each block, the participants were asked to limit (head and non-dominant hand) movements and keep fixation on the center of the screen where the stimuli were shown.

2.5 | Data Pre-Processing and Analysis

In the present study, we primarily focused on DDM, EEG, and their association using a joint modeling approach; accordingly, only these analyses and results are reported below (see Text S1–S4 and S6 for more details on additional analyses, including self-report measures, skin conductance, eye-tracking data, and task performance). For all SAT-related data analyzed separately, including eye fixations, behavioral performance (accuracy and RTs), and EEG, we followed the same pre-processing procedures as in previous studies (Verschooren et al. 2025; Wang et al. 2025). We removed training trials, trials in the practice block, warm-up trials, and the trials during which the sound was played. In addition, for all measures, except accuracy, we removed incorrect trials and the trials immediately following errors, as these may reflect post-error adjustments rather than the task-related processes of interest (Dali et al. 2022).

All frequentist statistical analyses reported below (and also in Data S1), including *t*-tests and repeated-measures (RM) ANOVAs, were conducted in R (R Core Team, 2025, version 4.3.3; RStudio Team, 2026.01.0) using the BruceR package (Bao 2021). For *t*-tests and post hoc comparisons, we calculated and reported 95% confidence intervals (CIs) for Cohen's *d* (Cohen's *d* for *t*-tests, for post hoc comparisons following RM ANOVAs, Cohen's *d* was computed using the root mean square error). For RM ANOVAs, we reported partial eta squared (η_p^2) together with 90% CIs, following common practice (Lakens 2013; Steiger 2004). Bonferroni correction was applied to adjust *p* values for multiple comparisons in RM ANOVAs. When the assumption of sphericity was violated, degrees of freedom were corrected using the Greenhouse–Geisser method.

2.5.1 | Drift Diffusion Model (DDM)

We analyzed the accuracy and RT data jointly, using a hierarchical drift diffusion model (HDDM), implemented in Python 3.7 and HDDM 0.9.9 (Wiecki et al. 2013). We followed the same preprocessing procedure described above. However, because accuracy was also used and coded at the single-trial level in this DDM, incorrect trials were retained, whereas trials immediately

following errors were removed (see Wang et al. 2025, for a similar procedure; see also Schmitz and Voss 2012, for a similar approach and discussion on removing post-error trials when using the DDM). In our previous study, the best model included the inter-trial variability of non-decision time (*st0*) and a fixed boundary separation (*a*) across conditions (Wang et al. 2025). This model (i.e., model #1 in the current study, see Table 1), allowed drift rate (*v*) and non-decision time (*t0*) to vary freely across Switch Type, Attention Type, and Condition, but with the starting point (*z*) fixed at the midpoint between the two response boundaries, which indicated that there was no response bias toward either the accurate or wrong response before stimulus onset. However, we also computed another model (i.e., model #2, see Table 1) with the boundary separation (*a*) varying across Switch Type, Attention Type, and Condition, while the other settings stayed the same as model #1. The reason for computing model #2 was that the results showed that hypervigilance modulated mostly accuracy rather than RTs (see Figure S6). Model comparison was performed between these two models (see Table 1). For them, we relied on a mixture model to deal with outliers in the data (5% of the data were assumed to be outliers, see Wiecki et al. 2013). All models were estimated through Markov Chain Monte Carlo (MCMC), where 5000 samples were drawn while discarding the first 1000 (as burn-in).

The best-fitting model was chosen based on the Deviance Information Criterion (DIC); the model with the smallest DIC was considered the best one. Model convergence was confirmed by visual inspection of the sampling traces and posterior distribution and with Gelman–Rubin statistics (Gelman and Rubin 1992) for each model separately (see details in Data S1). Furthermore, we also conducted posterior predictive checks to examine the model fit. We examined and reported the Bayesian proportion (i.e., p_{Bayes}) showing the difference between conditions for all parameters through Bayesian estimation using the built-in function in the HDDM package. It represents the probability of the posterior in which the parameter (e.g., drift rate) for one condition is greater or less than the other one (Wiecki et al. 2013). For convenience, a threshold of 0.05 (0.95) proportion of posterior is often used to decide whether one condition is greater or smaller than the other

TABLE 1 | Models' details and fit.

Model	Parameter setting	DIC
Model #1	<i>a</i>	–28520.619
	<i>v</i> : S×A×C	
	<i>t0</i> : S×A×C	
	<i>st0</i>	
Model #2	<i>a</i> : S×A×C	–28602.405
	<i>v</i> : S×A×C	
	<i>t0</i> : S×A×C	
	<i>st0</i>	

Abbreviations: A, Attention Type; *a*, boundary separation; C, Condition; DIC, Deviance Information Criterion, the model with the smallest DIC was considered the best one (i.e., model #2); S, Switch Type; *st0*, the inter-trial variability of non-decision time; *t0*, non-decision time; *v*, drift rate.

one. In the current study, we considered the proportion that is below 0.05 (or above 0.95) as strong evidence revealing a difference, while the proportion ranging between 0.05 and 0.1 (or 0.9–0.95) indicates sufficient but weak evidence supporting a difference between conditions (Pan et al. 2025; Wiecki et al. 2013).

2.5.2 | Electroencephalography (EEG)

EEG data was pre-processed through the MNE library (Gramfort et al. 2013) with Python (Python Core Team, 2020), and statistical analyses were carried out with R (R Core Team, 2025, version 4.3.3; RStudio Team, 2026.01.0). We first identified bad channels in the raw data (mean = 5.8%), which were excluded from the independent components analysis (ICA) and other preprocessing steps, and were interpolated at the end of preprocessing. The data were then band-pass filtered between 1 and 30 Hz (as recommended by MNE for subsequent independent component analysis) and down-sampled from 512 Hz to 250 Hz. Based on the recent EEG study on the SAT (Verschooren et al. 2025), we extracted cue-related epochs from 200 ms before to 1000 ms after cue onset, and target-related epochs from 200 ms before to 600 ms after target onset. We removed the epochs for warm-up trials, errors, and the trials following them, as well as the trials where the sound was played. Next, we ran an ICA, and the components corresponding to the blinks and horizontal eye movements were automatically selected and removed based on the four EOG channels. This automatic selection was manually inspected and corrected where necessary. After the ICA, we implemented an artifact rejection algorithm (*autoreject*) and applied a fixed peak-to-peak threshold (150 mV) to further correct or reject contaminated data segments (Jas et al. 2017). Finally, we interpolated the bad channels and re-referenced the data to the average of all electrodes. The average number of epochs kept for each condition separately is shown in Table S5.

The time window and electrode selection used to quantify the target-locked ERP components were defined a priori and based on Verschooren et al. (2025). In line with this study, we also examined the cue-related contingent negative variation (CNV). For this component, we selected electrodes Cz, FCz, C2, FC2, and FC4.² For the target-locked components, we selected electrodes PO8, P8, PO7, and P7 for the P1 component; electrodes O1, O2, Oz, and POz for the N1 component; electrodes PO8, P8, PO7, and P7 for the P2 component. Mean amplitudes were averaged across those selected electrodes within time windows centered on each component's peak, in line with Verschooren et al. (2025). For the cue-locked CNV component, the mean amplitude was calculated approximately 100 ms around the peak (923–1000 ms, peaked at 973 ms). For the target-locked P1 and N1 components, the time window was defined as 23.4 ms around the peak (P1: approximately 112–135 ms, peaked at 123.7 ms; N1: approximately 171–194 ms, peaked at 182.2 ms). For the target-locked P2 component, the time window was 82 ms around the peak (approximately 340–422 ms, peaked at 381.1 ms). We compared these mean ERP amplitudes using 2 (Switch Type: repeat, switch) $\times$ 2 (Attention Type: external, internal) $\times$ 3 (Condition: control, neutral, negative) RM ANOVAs.

2.5.3 | Joint Modeling Between ERP and DDM

We also employed a joint-modeling approach through the single-trial regression model between the drift rate (v) and the target-locked components, using the regression function in HDDM (Frank et al. 2015; Wiecki et al. 2013). Compared to the standard ERP analysis described above, another preprocessing was performed for this joint modeling because error trials were not excluded but actually held in this analysis (and in keeping with the preprocessing of the behavioral data for the DDM). However, training and warm-up trials, trials in which a sound was presented, and post-error trials were excluded. All other preprocessing steps were identical to those used for the standard ERP analysis described herein. Finally, the ERP and behavioral data were temporally aligned and combined with each other at the single-trial level for joint modeling.

In this analysis, we mostly focused, given our a priori hypothesis, on the P2 amplitude and its link to the drift rate (v). However, to confirm the specificity of this association, we also examined whether the P1 and N1 might also predict the drift rate. To this end, we extracted at the single trial level the mean amplitude of the P1, N1, and P2 components from the pre-selected electrodes (P1: PO8, P8, PO7, and P7; N1: O1, O2, Oz, and POz; P2: PO8, P8, PO7, and P7) during their respective time-interval following target onset (P1: 112–135 ms; N1: 171–194 ms; P2: 340–422 ms). The amplitudes of these three components were entered into the best HDDM model, respectively, to predict drift rate (v) alongside Switch Type, Attention Type, and Condition (also with 5000 samples and 1000 burn-ins). The output of this regression model contained coefficients estimating the effect of the ERP components on drift rate (v) for all conditions (Frank et al. 2015). To evaluate the predictive strength, we compared the posterior distributions of these coefficients against 0 through Bayesian estimation using the HDDM's built-in function (i.e., p_{Bayes}). A posterior greater than 0 indicated a positive prediction, while a posterior less than 0 suggested a negative relationship.

3 | Results

3.1 | DDM

Model #2, which included all three parameters (a , v , t_0) varying with the three-way interaction between Switch Type, Attention Type, and Condition, fit the data best (see Table 1, where model #2 shows the smallest DIC; also see the Text S8 for model convergence checks).³ This model replicated the pattern of results found in our previous study (see Wang et al. 2025), showing that the drift rate (v) captured an asymmetric switch cost (as consistently found in previous studies based on the SAT, e.g., Hautekiet et al. 2023; Verschooren et al. 2020, 2021; Verschooren et al. 2025; Verschooren, Liefvooghe, et al. 2019a; Wang et al. 2025) and, moreover, Condition substantially influenced it. Importantly, this asymmetry was not found in the negative condition, where there was no difference between switch and repeat trials for either of the two attention types (negative: $p_{\text{Bayes}}(\text{SI} > \text{RI}) = 0.10$, $p_{\text{Bayes}}(\text{SE} > \text{RE}) = 0.45$). Moreover, in line with reduced internal shielding, we found that participants had a lower drift rate (v) on repeat-internal trials in the negative compared to the control

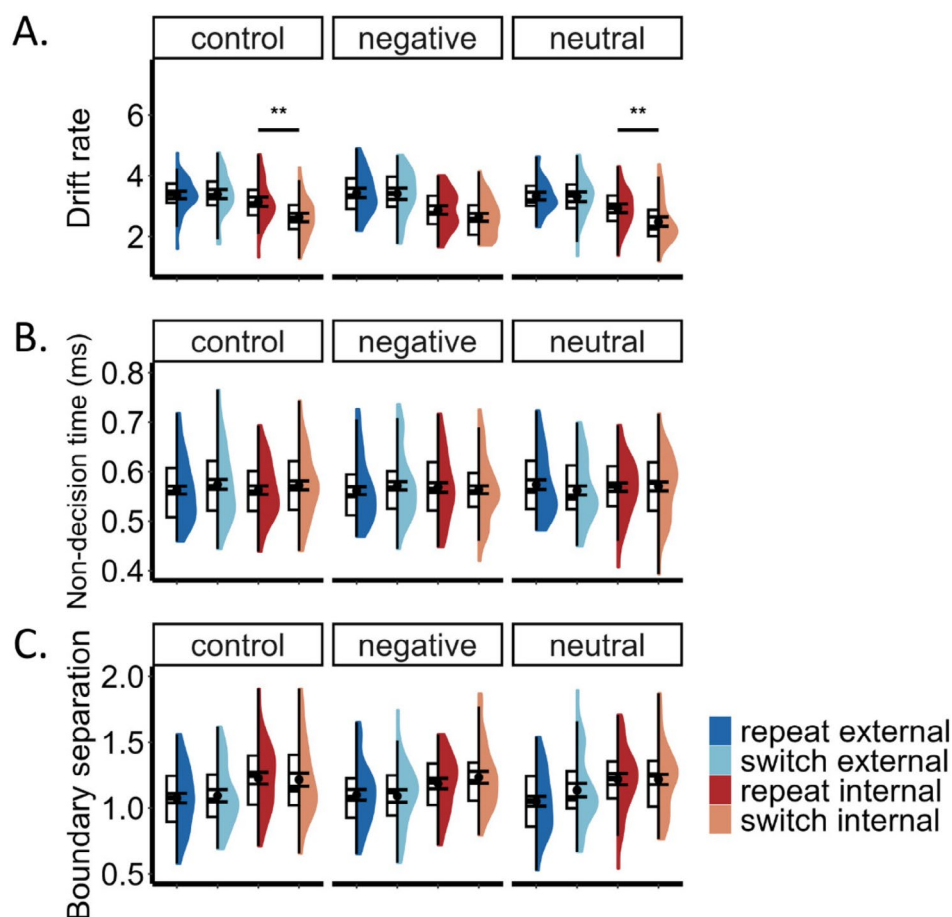


FIGURE 2 | DDM results. (A) Drift rate (v) for the different conditions separately: (B) Non-decision time (t_0): (C) Boundary separation (a). The error bars show mean $\pm$ within-subject 95% confidence interval (wsci). *** represents strong evidence ($p_{\text{Bayes}} > 0.95$ or $p_{\text{Bayes}} < 0.05$).

condition, while no difference was found on switch internal, repeat external, or switch external trials between conditions (repeat-internal: $p_{\text{Bayes}}(\text{negative} > \text{control}) = 0.078$). Regarding non-decision time (t_0), no difference was found, again replicating our previous results (Wang et al. 2025). Additionally, we found a larger boundary separation for internal than external trials in general, suggesting that participants were more cautious for internal than external trials (see Figure 2 and Table S4 for details).

3.2 | ERPs

For the early visual processing (i.e., target-locked P1 and N1 components), only the main effect of Attention Type on the N1 was significant (see Text S9 and S10, where these results, as well as those for the cue-locked ERP component—CNV—are reported). For the P2, the interaction between Switch Type and Attention Type was significant ($F(1, 45) = 20.83$, $p < 0.001$, $\eta_p^2 = 0.32$, 90% CI [0.14, 0.47]). The P2 amplitude in switch internal was larger than repeat internal trials ($t(45) = -4.42$, $p < 0.001$, Cohen's $d = -0.10$, 95% CI [-0.16, -0.03]), while the difference was not significant for external trials ($t(45) = 1.883$, $p = 0.25$, Cohen's $d = 0.04$, 95% CI [-0.02, 0.10]). Moreover and importantly, the three-way interaction between Switch Type, Attention Type, and Condition was significant for this ERP component ($F(2, 90) = 3.14$, $p = 0.049$, $\eta_p^2 = 0.065$, 90% CI [0, 0.15]). Post hoc comparisons showed a

significant interaction between Switch Type and Attention Type in both the control and neutral conditions (control: $F(1, 45) = 19.87$, $p < 0.001$, $\eta_p^2 = 0.31$, 90% CI [0.13, 0.47]; neutral: $F(1, 45) = 8.30$, $p = 0.006$, $\eta_p^2 = 0.16$, 90% CI [0.03, 0.32]), during which the P2 amplitude was larger for switch internal than repeat internal trials (control: $t(45) = -3.36$, $p = 0.007$, Cohen's $d = -0.13$, 95% CI [-0.24, -0.02]; neutral: $t(45) = -3.61$, $p = 0.003$, Cohen's $d = -0.13$, 95% CI [-0.24, -0.02]), while there was no significant difference for external trials (control: $t(45) = 2.41$, $p = 0.07$, Cohen's $d = 0.09$, 95% CI [-0.02, 0.20]; neutral: $t(45) = 1.02$, $p = 0.94$, Cohen's $d = 0.04$, 95% CI [-0.06, 0.14]). However, in the negative condition, this interaction was not significant ($F(1, 45) = 0.18$, $p = 0.67$, $\eta_p^2 = 0.004$, 90% CI [0, 0.08]). There was no difference between repeat and switch for both external and internal trials (external: $t(45) = -0.69$, $p = 1.00$, Cohen's $d = -0.03$, 95% CI [-0.16, 0.10]; internal: $t(45) = -0.13$, $p = 1.00$, Cohen's $d = -0.006$, 95% CI [-0.13, 0.01]) (see Figure 3).

3.3 | Joint Modeling

The results showed that for all three ERP components under consideration, their amplitude predicted the drift rate. This relationship was positive for the P1 and P2 ($p_{\text{Bayes}(n > 0)} = 1$), while it was negative for the N1⁴ ($p_{\text{Bayes}(n > 0)} = 0$). To assess whether hypervigilance influenced the ERP-behavior relationship, we compared the coefficients of each ERP component between

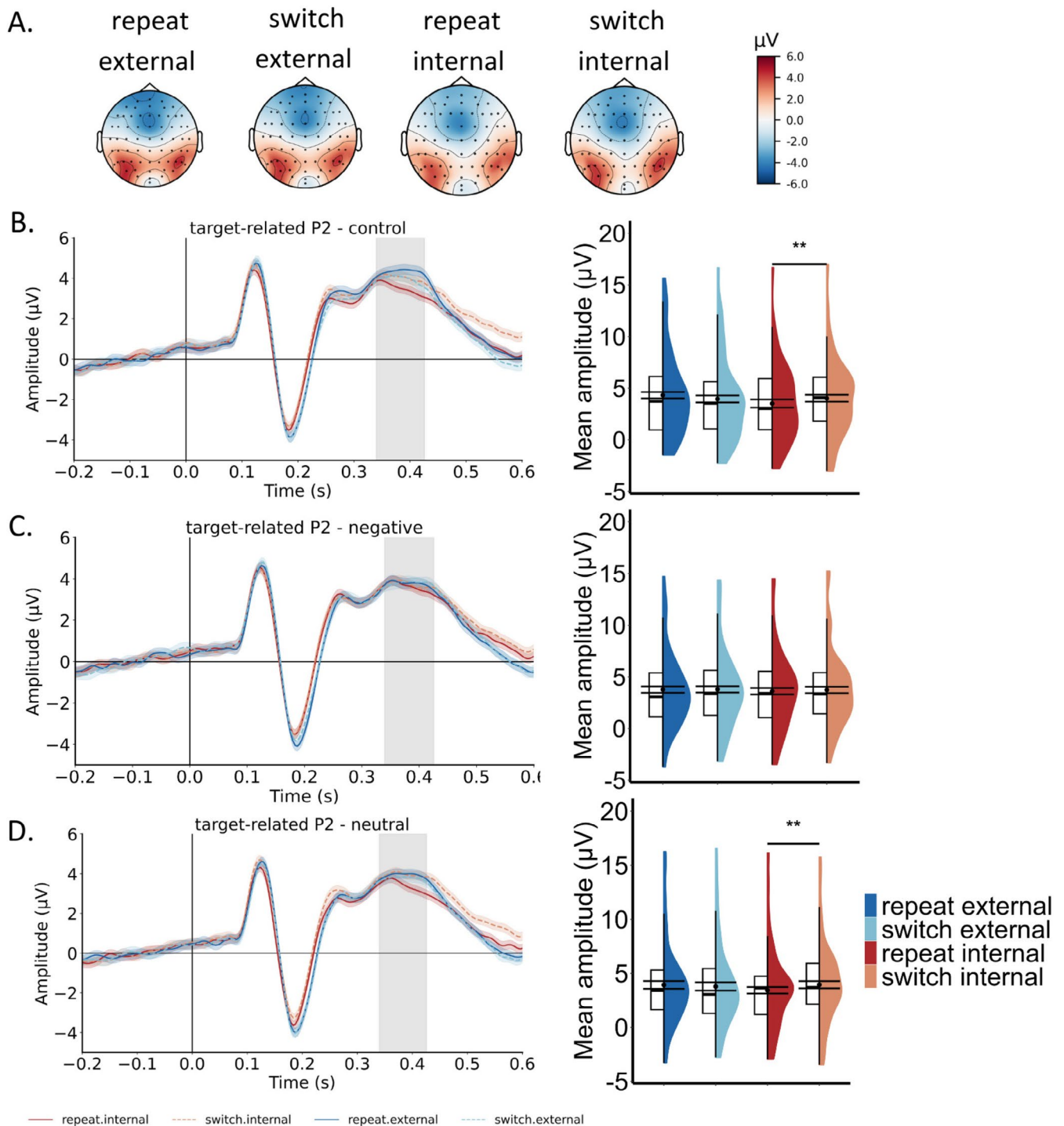


FIGURE 3 | Target-locked ERPs with a focus on the P2. (A) The topography for the P2 component is shown for four main conditions separately (i.e., repeat external, switch external, repeat internal, switch internal). (B) The averaged target-locked ERP waves (left panel, electrodes PO8, P8, PO7, and P7) and P2 amplitude (right panel) for the control condition are shown. For the ERP waves, the P2 is highlighted by the shaded area (left panel). (C) They are shown for the negative condition. (D) The neutral condition is shown. The error bands/bars show mean $\pm$ wsci. *** represents $0.01 < p < 0.001$.

the four trial types (i.e., repeat external, switch external, repeat internal, switch internal) within each condition (i.e., control, negative, and neutral). For the P2, this relationship changed in the negative condition compared to the two other ones (see Figure 4). More specifically, compared to the control and neutral conditions, the coefficients for repeat internal trials were

selectively reduced compared to the three other trial types (see Table S6: P2).

For the P1 and N1, different results were found compared to the P2 (see Figures S13 and S14). For the P1, a larger coefficient for the switch external trials than the three other trial types was

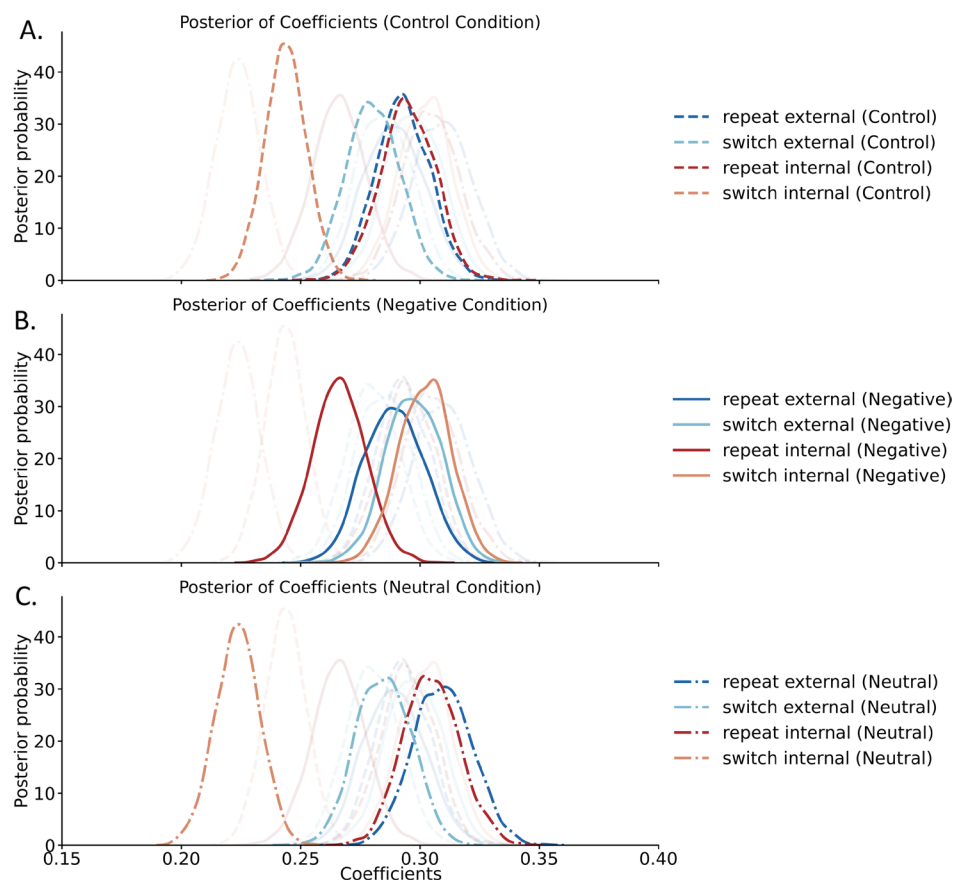


FIGURE 4 | Joint ERP-DDM modeling (P2). The posterior distributions of the coefficients for each condition are displayed across all subplots, with only the relevant coefficients highlighted for each condition (i.e., control, negative, and neutral). (A) The four main conditions (i.e., repeat external, switch external, repeat internal, switch internal) are shown for the control condition with dashed lines in the brighter color. (B) The same four conditions are shown with solid lines in the brighter color for the negative condition. (C) The neutral condition is shown with dot-dashed lines in the brighter color (also the same four conditions). As can be seen, for the negative condition selectively, the coefficient for repeat internal trials was reduced compared to the three other trial types. This effect was not observed for the control and neutral conditions.

found in both the neutral and negative conditions (see Table S6: P1). This pattern was distinct from the N1, for which, in the negative condition, the coefficients for external trials decreased compared to the other trial types (i.e., an increase in absolute values, see Table S6: N1).

4 | Discussion

In this study, we examined the neurophysiological mechanisms underlying hypervigilance's effect on attentional balance. Successful hypervigilance induction was confirmed indirectly through the sound ratings and the SCR, replicating our previous findings (Wang et al. 2025). Moreover, distinct eye fixation patterns were also observed between external and internal trials, with the latter ones associated with fewer and longer fixations, as well as denser fixation distribution compared to the former ones. These eye fixation results suggest perceptual decoupling for internal trials, corresponding to a disengagement from sensory information in this condition, and as previously found (Benedek et al. 2017; Ceh et al. 2020, 2021; Korda et al. 2023, 2024; Schooler et al. 2011; Servais et al. 2022; Smallwood and Schooler 2006). Interestingly, we found this pattern for both the target and preceding cue,

suggesting that during internal attention, the participants were likely already prepared to disengage from the external input at the cue level to facilitate memory retrieval (Walcher et al. 2017). In agreement with this interpretation, the cue-locked CNV and target-locked N1 showed that the participants prepared more for internal than external trials after the cue onset, leading to a stronger reduction of sensory processing for these internal trials following the target: two ERP effects that were already reported with the SAT previously (Verschooren et al. 2025).

Moreover, at the behavioral level, we replicated our previous DDM findings (Wang et al. 2025), showing that hypervigilance led to a lower drift rate (v) for repeat internal trials, selectively (while the non-decision time remained unaffected), which eventually yielded a 'symmetric switch cost' in the negative condition. As we previously advocated (Wang et al. 2025), this result can be interpreted as reflecting an impaired shielding efficiency for internal attention under hypervigilance. Notably, by using EEG, we found that this impaired internal shielding associated with hypervigilance was not captured by the target-locked N1 (or P1 component); instead, we found that the subsequent P2 component did so. Closely aligned with the drift rate results, the interaction between Attention Type and

Switch Type was absent for the P2 amplitude in the negative condition, whereas in the control and neutral conditions, this two-way interaction was clearly expressed. Because the P2 was recently proposed to capture internal shielding during attentional balance (Verschooren et al. 2025), our new ERP results not only confirm this interpretation, but they also show for the first time that hypervigilance selectively influences this process by decreasing it. Crucially, our joint modeling analyses reinforced this conclusion. Under hypervigilance, the trial-by-trial relationship between P2 amplitude and drift rate was selectively weakened for internal repetition trials, directly linking the altered neural signal to the behavioral mechanism of impaired shielding (Frank et al. 2015; Verschooren et al. 2025; Wang et al. 2025). This selective change under hypervigilance was specific for the P2 because neither the P1 nor the N1, although both were also related to the drift rate, showed this same pattern. Moreover, a control analysis confirmed that this P2 component did not simply correspond to an early P3 component; the latter one was clearly expressed at a later time point following target onset and with a different topographical expression compared to the P2 (See Text S11). Taken together, these results pinpoint the P2 as the (neural) process during which the default internal shielding benefit found during attentional balance is temporarily compromised by hypervigilance. Moreover, they extend the functional interpretation of the drift rate (v) in ERP-DDM associations: beyond indexing evidence accumulation during decision-making, drift rate may also reflect a critical shielding mechanism that supports attentional switching (Nunez et al. 2015, 2024; Karayanidis et al. 2023; Schmitz and Voss 2012; Wang et al. 2025).

Although hypervigilance did not directly impact the P1 and N1 components, our joint modeling results revealed a subtle influence of this negative affective state on the N1, indicating that its effects actually occurred before the P2 component. For the P1, stronger associations with drift rate (v) were observed when switching to external attention in both the neutral and negative conditions, which involved a safe/aversive sound played unpredictably during the SAT. This pattern suggests that the P1 modulation during the SAT may reflect a general attentional (or even arousal) effect. As an early sensory component modulated by top-down attention (Hopfinger et al. 2004; Luck 1995; Niu et al. 2008), the P1-drift rate link may reflect early attentional allocation, affected by the sound or uncertainty (Schmitz and Grillon 2012). In comparison, the N1-drift rate association increased for external trials under hypervigilance, likely suggesting a facilitation of external attention (consistent with previous EEG studies, Michalowski et al. 2009; Weymar et al. 2014). Given N1's role in perceptual decoupling, these findings may reflect strengthened external coupling under hypervigilance, though not strong enough to appear in averaged ERP signals (Dehaene and Changeux 2005; Schooler et al. 2011; Verschooren et al. 2025).

Combined together, these new joint-modeling results therefore suggest the contribution of three distinct processes to attentional balance and its progressive modulation by hypervigilance. First, an unspecific attentional or arousal effect appears to influence the P1 component during the SAT. Second, hypervigilance influences perceptual decoupling at the N1

level, mostly by increasing external processing. Interestingly, this change culminates in an impaired shielding benefit for internal attention, which is best captured by the P2 component. Hence, these novel ERP results suggest that whereas hypervigilance leaves the P1 unaffected, it does influence the subsequent N1 and P2 ERP components, yet with dissociable effects for them (i.e., perceptual decoupling—N1 vs. internal shielding—P2) (see Figure 5). Notably, the earlier modulation of the N1-drift rate association (compared to P2) raises the question of a causal or temporal link between these two processes. Although computationally demanding, future studies could benefit from modeling these components concurrently to better disentangle their respective roles in attentional balance under hypervigilance. Furthermore, given that hypervigilance is a hallmark of some affective disorders (APA 2013; Zeigler-Hill and Shackelford 2020), these findings also hold clinical relevance. If hypervigilance impairs internal shielding, then beyond interventions aimed at reducing external attentional bias (such as attention bias modification, see Mogg et al. 2017), strategies such as working memory training or mindfulness, shown to improve attentional control, may yield beneficial effects for affective disorders characterized by an excessive use or presence of this specific attentional state, such as generalized anxiety disorders (Beloe and Derakshan 2020; Cameron and Mamon 2019; MacLeod and Clarke 2015; Prakash et al. 2020).

There are some limitations that warrant comment. First, compared to our previous study where hypervigilance mostly influenced RTs during the SAT (Wang et al. 2025), here we found that accuracy actually captured its effect on attentional balance because the participants were overall more cautious compared to this previous study (see Text S7), for reasons that remain currently unclear. However, since we used a DDM where both speed and accuracy at the single trial are considered (Ratcliff 1985) and we replicated our previous results (i.e., modulation of the drift rate, while non-decision time did not vary), we are confident that these differences likely reflect uncontrolled variability or noise between these two studies, as opposed to genuine differences regarding the cognitive process under consideration (i.e., attentional balance). Second, and as already noted in our previous study (Wang et al. 2025), whether hypervigilance per se, as we argue, or perhaps another negative affective state or component, eventually accounts for these neurophysiological results remains to be confirmed in future studies. Although we employed the same hypervigilance manipulation as in our previous study and supplemented it with additional measures (i.e., some items drawn from the MASQ), these self-report data did not indicate a clear increase of anxious arousal in the negative relative to the neutral condition. Hence, some caution is needed regarding the induction of hypervigilance, as these measures (i.e., subjective ratings) did not confirm it unambiguously. However, the eye-tracking results showed that the participants in the negative condition exhibited fewer but longer fixations during both cue and target phases, which are compatible with a hypervigilant scanning strategy characterized by reduced eye movements (Eysenck 1992; Richards et al. 2014). At the same time, we acknowledge that this differential eye fixation pattern found in the negative condition may also reflect oculomotor freezing and/or the expression of a fear-related state in this

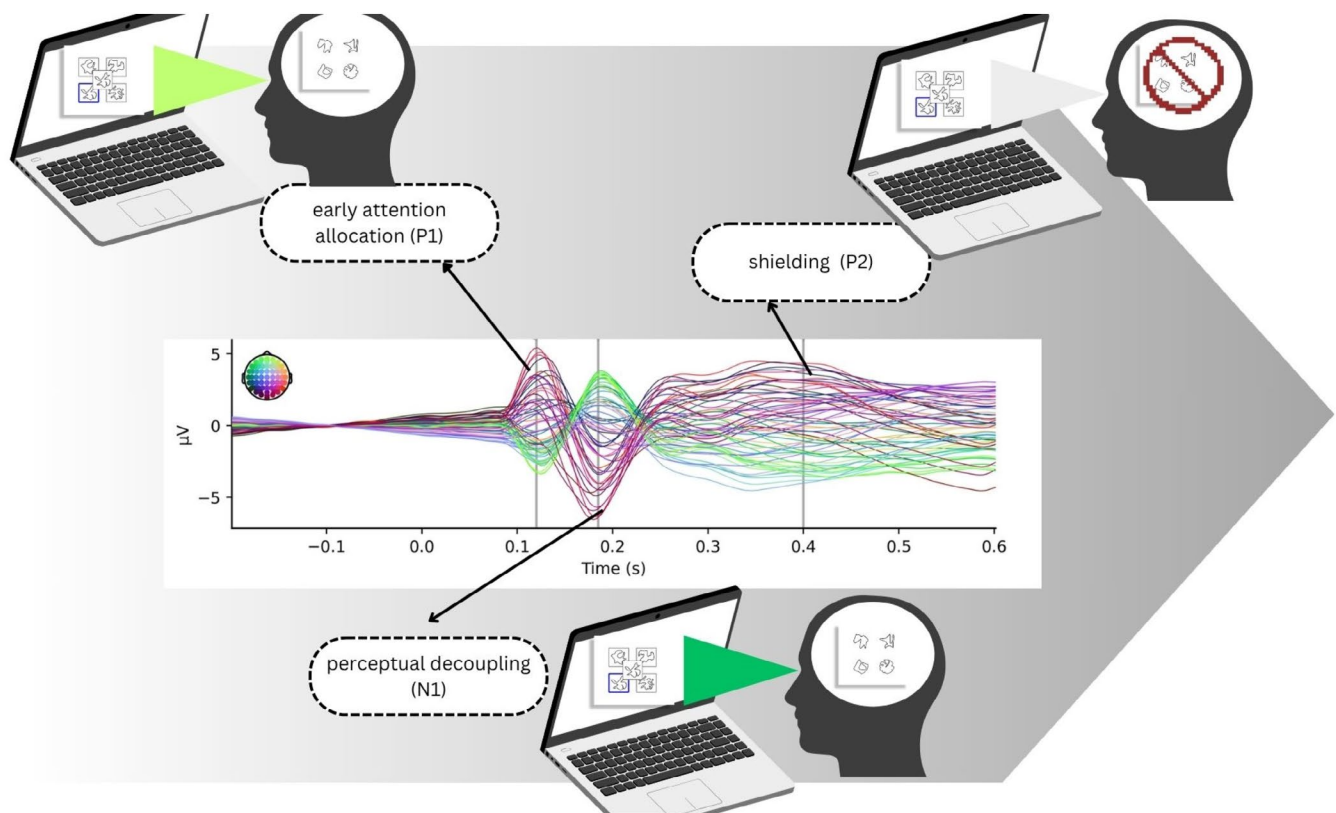


FIGURE 5 | Summary of the main (target-related) ERP effects found in this study, and their link to attentional balance as well as hypervigilance. Whereas the early (external) attention allocation/orienting to the target (P1) is influenced by an unspecific arousal or uncertainty effect (light green triangle), perceptual decoupling (N1) and internal shielding (P2) are both influenced by hypervigilance, yet with dissociable effects found for them. At the N1 level, the perceptual coupling with external attention is enhanced by hypervigilance (green triangle). However, at the P2 level, a selective internal shielding impairment is found under hypervigilance (green triangle and red circle).

condition (Grillon 2008; Merscher and Gamer 2024; Rösler and Gamer 2019). Hence, although the eye fixation results clearly showed a distinct pattern in the negative compared to the neutral and control conditions, their actual interpretation also requires caution. Additional studies are needed to assess whether this eye fixation pattern captures hypervigilance or perhaps another affective component or response (such as freezing). Lastly, while differences in eye fixations between internal and external trials (potentially due to perceptual decoupling; Korda et al. 2024) might raise concerns about their contamination of ERPs (such as the N1 or P2), additional control analyses suggested that this is unlikely because no significant correlations were found between eye fixations and N1/P2 amplitudes (see Text S5), nor did fixation distributions align with P2 differences across conditions (see Figure S4). This dissociation is also consistent with previous studies reporting either no correlation between the eye-tracking measures and the neurophysiological (MEG) data for attentional balance (see Gresch et al. 2024b, where the authors used a different task), or preserved alpha modulation for internal attention in the absence of microsaccades (Liu et al. 2022). That said, further research is needed to clarify the potentially complex, non-linear relationship between eye fixations and early visual ERPs during the SAT (Dimigen and Ehinger 2021).

In sum, this study shows that hypervigilance influences attentional balance by reducing internal shielding selectively. This

process is captured by the drift rate using a DDM (with a specific modulation of this parameter for repeat internal trials under hypervigilance) and by the P2 ERP component. Interestingly, a joint modeling approach further corroborates the intriguing association between these two effects, providing novel insights into the brain mechanisms through which this negative affective state influences attentional control.

Author Contributions

Gilles Pourtois: conceptualization, methodology, supervision, writing – review and editing. **Sam Verschooren:** conceptualization, methodology, writing – review and editing. **Nan Wang:** conceptualization, methodology, investigation, formal analysis, writing – original draft.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Open Science Framework at <https://doi.org/10.17605/OSF.IO/SFXCA>.

Endnotes

¹The eye with the best calibration accuracy was selected for each participant (32 left eye and 14 right eye) and was kept constant throughout the experiment. Given that the SAT requires central fixation, no systematic differences between left- and right-eye recordings were expected.

²For the cue-locked CNV component, we removed one electrode (i.e., FC6) compared to Verschooren et al. (2025) because the topography turned out to be slightly different (see Figure S9A).

³See Text S2, S4, S6 for the separate results concerning the self-report measures, skin conductance, eye fixations, and task performance (RTs, accuracy).

⁴Since the N1 is a negative component, a negative relationship with the drift rate was expected.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1: Section 1:** Manipulation checks (self-report measures and skin conductance). **Table S1:** Self-reports items. **Text S1:** Data pre-processing and analysis. **Text S2:** Results. **Section 2:** Eye fixations. **Text S3:** Data pre-processing and analysis. **Text S4:** Results. **Text S5:** Additional analysis. **Section 3:** Reaction times (RTs) and accuracy. **Text S6:** Results. **Text S7:** Additional analysis. **Section 4:** DDM. **Text S8:** Model convergence checks. **Table S4:** Bayesian testing for the Posterior in model #2. **Section 5:** EEG. **Table S5:** Number of trials kept after pre-processing for eye fixations and EEG. **Text S9:** Cue-locked contingent negative variation (CNV). **Text S10:** Target-locked P1 and N1. **Text S11:** Targetlocked P3. **Section 6:** Joint Models between target-locked ERPs and drift rate (v). **Figure S13:** Joint model between P1 and drift rate (v). **Figure S14:** Joint model between N1 and drift rate (v). **Table S6:** Bayesian testing for the joint model.