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RESEARCH

Hypervigilance strikes a balance between external and internal attention: behavioral and modeling evidence from the switching attention task

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Abstract
Hypervigilance involves increased attentional scanning of the environment to facilitate the detection of possible threats. Accordingly, this state is mostly bound to external attention and as a corollary, it might be detrimental to internal attention and further affect attentional balance defined as the ability to switch dynamically between these two domains. In the current study, we aimed to address this question and induced hypervigilance in 49 healthy participants through the presentation of a task-unrelated aversive sound while they performed the switching attention task (SAT), which was previously devised to study attentional balance. The skin conductance response results, as well as subjective sound ratings, confirmed that the hypervigilance manipulation was successful. At the behavioral level, hypervigilance led to a more symmetrical balance between internal and external attention compared to the control and neutral conditions, where it was asymmetrical, replicating previous studies. Moreover, using a drift diffusion model, we found that hypervigilance reduced the drift rate for internal repetition trials, suggesting that hypervigilance possibly caused an impaired shielding of internal attention.

Imagine that you have just finished watching a horror movie at home and decide to head to the kitchen for a snack. As you are still immersed in the movie plot of the serial killer, a sudden noise startles you. You start to scan for the source of the sound and look for possible dangers in the room. After scanning the room thoroughly and going back to your bedroom empty-handed, you wonder: "What was that sound? Why did I come to the kitchen anyway?…" This example illustrates the effects hypervigilance has on cognition and how it affects attention more specifically. Hypervigilance is a distinctive attentional control state involving increased scanning of the environment to facilitate the detection of possible threats, thereby increasing survival (Richards et al., 2014; Schulkin & Rosen, 1998). Different from the selective attention to threat, which is associated with the orienting network, it is related to the alerting network, which ensures sustained alertness and increased readiness to detect and process danger (Dolan & Vuilleumier, 2003; Fan et al., 2005; Posner & Rothbart, 2007; Richards et al., 2014). In laboratory settings, it is often triggered by aversive stimuli, including electric shocks, loud noises, or airblasts, which all have the propensity to increase arousal at the physiological level and are typically disliked at the subjective level because increasing state anxiety (Davis et al., 2010; Grillon, 2008; Grillon et al., 2004; Grillon & Ameli, 1998). At the autonomic nervous system (ANS) level, increases in the heart rate and the skin conductance response (SCR) are often used to corroborate the induction of arousal that can result from hypervigilance (Grillon et al., 2004; Siegel et al., 2018).

Moreover, hypervigilance is related to specific neurological or psychopathological conditions, including chronic pain (Chapman, 1978) and anxiety (Eysenck, 1992; Eysenck et al., 2007). Patients with chronic pain are often hypervigilant

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to pain or pain-related information (Crombez et al., 2005), which likely results from both an enhanced engagement to as well as difficulty in disengaging from pain signals (Van Damme et al., 2006). Similarly, pathological anxiety, which is defined as an exaggerated fear, is also characterized by hypervigilance (Rosen & Schulkin, 2022; Schulkin & Rosen, 1998). In this affective condition, the normal fear reaction to a possible danger or threat is amplified and becomes sustained and chronic, leading to hyperactivation of limbic fear circuits in the human brain (Grillon, 2008), which is accompanied by a decreased prefrontal cortex control and regulation (Grupe & Nitschke, 2013). Furthermore, it also involves hyperarousal indexed by enhanced activation of the sympathetic nervous system and blunted hypothalamic-pituitary-adrenal activity (Kleshchova et al., 2019; Yoon & Weierich, 2016).

Hypervigilance primarily reflects a change in attention where the perceptual processes are heightened and hence the processing of threat-related stimuli is prioritized (Cornwell et al., 2017). As mentioned above, the stimuli that induce hypervigilance are typically external or exteroceptive in nature which might suggest that this distinctive attentional control state is mostly bound to external attention (unlike pain-related hypervigilance, which is characterized by increased attention for internal events like bodily signals; see Peters et al., 2000). As a corollary, hypervigilance could be detrimental to the selection and processing of information held in memory (Shackman et al., 2006; Vytal et al., 2012), which necessarily requires internal attention (Chun et al., 2011). Attention can broadly be conceived as the cognitive mechanism through which information processing is steered and organized, and it can be deployed either to the external senses (external attention) or internal representations (internal attention) (Chun et al., 2011; Kiyonaga & Egner, 2013; Lim & Pratt, 2023; Oberauer, 2019; Ziegler et al., 2018). Moreover, attention is a multi-level system that attaches different weights to different types or streams of information with the goal of balancing and regulating their processing (Narhi-Martinez et al., 2023). As a result of this regulation, possible interactions between different sources or streams of information are reduced, thereby lowering the distraction or competition created between them. For example, such a regulation likely enables to shield information stored in working memory from irrelevant sensory information or long-term memory (Kiyonaga & Egner, 2013; Verschooren et al., 2021). In this framework, attentional balance corresponds to the ability to switch dynamically and frequently between these two domains to yield optimal information processing in each of them (Narhi-Martinez et al., 2023; Verschooren et al., 2019). However, an unanswered question is whether hypervigilance could influence attentional balance, and if true, in which direction.

Recently, the switching attention task (SAT) has been devised and validated to explore attentional balance in healthy volunteers at the behavioral level (Verschooren et al., 2019, 2020). During the SAT, participants are cued on a trial-by-trial basis to process either external visual stimuli or stimuli retrieved from visual memory (as achieved using a separate encoding phase), with a random presentation of these two trial types. On external trials, participants have to direct attention externally to visual stimuli presented on screen to perform a simple two-alternative forced-choice discrimination task based on stimulus identity. On internal trials, the exact same task is used, but it has to be performed by directing attention internally to visual memory instead. In other words, the exact same task is used throughout but needs to be based either on external or internal information. Through the transitions between these trials, four main conditions can be established and compared to each other at the statistical level: repeat external, repeat internal, switch external, and switch internal trials. Whereas on repeat trials, the same type of attention, either external or internal, is repeated across consecutive trials, switch trials involve a change of the attention type from one trial to the next one. More specifically, on switch external trial, participants moved from an internal to an external trial, with an opposite direction on switch internal trials. Using the SAT, Verschooren et al. (2019) found a substantial reaction time (RT) cost on these switch trials compared to the repeat ones. Notably, this cost was significant only for internal trials, reflecting a switch cost asymmetry: the difference between switch and repeat trials was larger for internal than external attention.

Based on a series of behavioral experiments that pitted different explanations against each other, it was suggested that this outcome could be explained by associative interference (Verschooren et al., 2020). According to this account, different memory traces for external and internal attention are learned associatively during the SAT, which can lead to interference between them. The asymmetric switch cost described here above implies that this interference is likely imbalanced. On switch trials, no matter the direction of the transition, working memory update takes place, thereby increasing vulnerability to interference from the competing attention type (Dreisbach & Wenke, 2011; Liefooghe et al., 2008). In comparison, on repeat trials, information in working memory needs to be maintained, and this is the process (i.e. maintenance) that could show a differential vulnerability to interference from the competing attention type (Verschooren et al., 2020; Verschooren & Egner, 2023). Compared to repeat external trials where this maintenance is supposedly shallow, on repeat internal trials, a deeper maintenance is obviously required, which therefore eases interference from external attention, in turn causing a larger switch cost (defined as the difference between repeat and switch trials) for internal than external attention. Interestingly, in a recent study (Gresch et al., 2024), the authors used a different task and also focused on switching between perception (i.e., external attention) and working memory (i.e., internal attention) and reported a similar asymmetric switch cost, yet mostly on error rates. In that study, switching was explored using a spatial attention (re) orienting paradigm with two cues within the same trial, as opposed to trial-by-trial transitions (and a single cue) with the SAT. Their results showed a larger cost when switching from perception to working memory than vice versa, which was also interpreted as reflecting an asymmetric interference between these two attention types.

According to the Internal Dominance over External Attention (IDEA) hypothesis (Verschooren & Egner, 2023), this asymmetry between external and internal attention can also be explained by the fact that human subjects are probably more strongly dominated or influenced by internal than external information processing, making it easier for internal attention to shield interference stemming from external attention or conversely increase distraction from internal information when external attention is used. Furthermore, this assumption accords well with previous findings and models showing that internally oriented attention or working memory can easily and swiftly guide or influence external attention, and shield distraction from perceptual information (Kiyonaga & Egner, 2013; Narhi-Martinez et al., 2023; Olivers et al., 2006).

The goal of the current study was to assess possible changes in attentional balance as a function of hypervigilance. Hypervigilance was induced by means of a task-irrelevant aversive sound (i.e., startle probe) played unpredictably several times, as used in a previous study (Rossi & Pourtois, 2014). As a neutral condition, we used a safe sound. Moreover, to explore whether sound delivery as such could create an unspecific interference effect on attentional control, we also used a control condition devoid of sound. Besides subjective ratings, we also used the SCR (to the sound) to confirm that arousal increased under hypervigilance (Bradley et al., 2001; Grillon et al., 2004, 2006). Furthermore, to examine whether state anxiety would increase in the negative condition, we also used the spontaneous eye blink rate because previous studies have linked it to anxiety, tension or stress (Giannakakis et al., 2017; Harrigan & O'Connell, 1996; Rossi & Pourtois, 2012). In those studies, the eye blink rate increased when anxiety or stress increased. We hypothesized that because hypervigilance creates an outward focus of attention which might jeopardize internal attention, the previously observed asymmetric switch cost would be smaller in this condition compared to the neutral and control conditions. That is, hypervigilance would tip the balance towards external attention and create a more symmetric control between external and internal attention, thereby decreasing the cost when moving from external to internal attention compared to the neutral and control conditions.

Moreover, to gain insight into the cognitive processes giving rise to these changes in attentional balance depending on hypervigilance, we also analyzed the task data using a Drift Diffusion Model (or Diffusion Decision Model; DDM). This model can estimate latent cognitive processes critical for decision-making (Ratcliff, 1978, 1979, 1985; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998). The estimation is based on the distribution information of RT of both correct and incorrect responses, enhancing data utilization by incorporating both accuracy and RT speed into the modeling process (Voss et al., 2013). Although there are different variants of the DDM that differ among other things along the number of parameters used, four of them have received a lot of attention in previous cognitive research, including response bias (starting point, z), response caution (boundary separation, a), processing efficiency (drift rate, v), and encoding and motor execution time (non-decision time, t0) (Ratcliff & McKoon, 2008; Voss et al., 2004, 2013). By modeling behavioral performance during the SAT, we could decompose the different cognitive processes responsible for switching between internal and external attention, and assess their susceptibility to hypervigilance (see Schmitz & Voss, 2011 for a similar approach in task switching).

When DDM is used to model the behavioral data in a situation where participants frequently need to switch between two domains or states based on a specific cue provided before the target (e.g., task switching), as done here in this study with the SAT, the primary parameters of interest are boundary separation (a), non-decision time (t0) and the drift rate (v) (Hartanto & Yang, 2022; Karayanidis et al., 2009; Schmitz & Voss, 2011, 2014). Since we did not have clear predictions about attention type (external or internal attention) and hypervigilance on response caution (i.e. boundary separation), we mainly focused on the two other parameters to assess whether hypervigilance could change either the cue-related (non-decision time, t0) or the target-related processing (drift rate, v). We expected to find similar effects in the control and neutral conditions: drift rate would be lower for switch internal than repeat internal trials (with the opposite direction found for the non-decision time), and this difference would be smaller for external trials. However, in the negative condition, a smaller asymmetry (or even no asymmetry) was expected for both parameters, if hypervigilance could modulate the balance between external and internal attention. Compared to the control and neutral conditions, we also predicted a lower drift rate (v) for internal and a higher one for external trials under hypervigilance (as well as for the non-decision time (t0), which might also increase for internal and decrease for external trials as a function of hypervigilance), as it might facilitate external attention by restricting the use of or access to internal attention.

Method

Participants

To increase statistical power and reach strong evidence (i.e., Bayes factor larger than 10) for the modulation of attentional balance as a function of hypervigilance, we ran a Bayesian sequential analysis to set the final sample size. However, we first used MorePower (MorePower, Campbell & Thompson, 2012) to estimate a minimum sample size when a repeated measures analysis of variance (RM ANOVA) to detect an effect size of 0.18 (partial η^2, calculated based on Verschooren et al., 2020) with 90% power was used. This analysis showed that at least 32 participants had to be included in the sample. Accordingly, we first recruited 32 participants. Then we added participants to this minimum sample until we reached strong evidence (five to eight participants each time, see Supplementary Figure S1), which turned out to be the case after we had included 49 participants. In total, we tested 53 participants (data collected in 2023). Four of them were removed from the subsequent analyses due to data loss and low accuracy (below 60%)[1]. The 49 participants retained (29 females) were aged between 18 and 25 (mean age = 20.103, sd = 1.809). They all had normal or corrected-to-normal vision, were unaware of the purpose of the study, and declared no history of psychiatric or neurological disorders, nor the use of psychoactive medication. Participants signed an informed consent and received either course credit or €10 for their participation. The study protocol was approved by the local ethics committee (#2022-097).

Design

The experiment used a 2 (Switch Type: repeat, switch) × 2 (Attention Type: external, internal) × 3 (Emotion: control, neutral, negative) within-subject factorial design. The experiment was divided into three sessions, corresponding to the three conditions. Their order (i.e. Control-Negative-Neutral, Negative-Neutral-Control, or Neutral-Control-Negative) was counterbalanced across participants. The interaction between Switch Type and Attention Type was coded on each and every trial, i.e., repeat external, repeat internal, switch external, or switch internal trials. For repeat trials, the Attention Type of the current trial stayed the same compared to the previous trial, while for switch trials, it changed (see Fig. 1a). The trial order was random but also counterbalanced within each session to create an equal number of trials in each of the four conditions.

Stimuli and procedure

The SAT (Verschooren et al., 2020) was programmed with psychopy (version 2022.2.4, Peirce et al., 2019). Sixteen non-verbalizable figures from a set created by Endo and colleagues (Endo et al., 2003) were chosen and used. These figures were shown on a white background screen of 1024 × 768 pixels (monitor: 40.5 cm × 30 cm). They were divided into four sets, each composed of four figures. Half of the participants used two sets (one for external and the other one for internal trials), while the other half used the two other sets to avoid any systematic effects between these figures and either Attention Type or Switch Type.

The experiment started with a training phase to familiarize the participants with the task and allow them to encode four figures in visual memory (i.e., internal attention). To equate the familiarity with the external and internal stimuli, we also included an external training phase (Verschooren et al., 2019). Participants started either with the external or the internal training phase (counterbalanced over participants). During the external training trials, the four figures appeared on screen surrounding a fifth, central figure (see Fig. 1b). Participants needed to perform a same-different matching task between the central figure (probe) and the one highlighted in the close periphery (target), whose location varied across trials. For the internal training phase, participants were first shown the four internal stimuli and instructed to commit the stimuli and their location to memory. After this self-paced memorization, on each internal training trial, the four (peripheral) figures were scrambled, and to perform the (same) matching task, they had to use internal attention for the four figures they had to learn to decide whether the scrambled figure highlighted was the same or different compared to the (central) probe (see Fig. 1c). If they made a mistake on an internal training trial, the four figures (unscrambled) appeared on the screen again (to provide another opportunity to consolidate them in visual memory). For both internal and external training phases, an 85% (mean) accuracy cutoff had to be reached before the participants could move to the next phase (and a minimum of 18 corrected trials needed to be completed).

After the training phase, participants moved to the experimental phase, which consisted of one practice block, and nine experimental blocks of 82 trials each. The task was the same for the practice block and test phase, except that a performance feedback (i.e. either "correct" or "incorrect")

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[1] Participants were excluded primarily based on accuracy, with those scoring below 60% in any of the twelve conditions being removed. This exclusion process was carried out after each test batch, which involved 5–8 participants at a time.

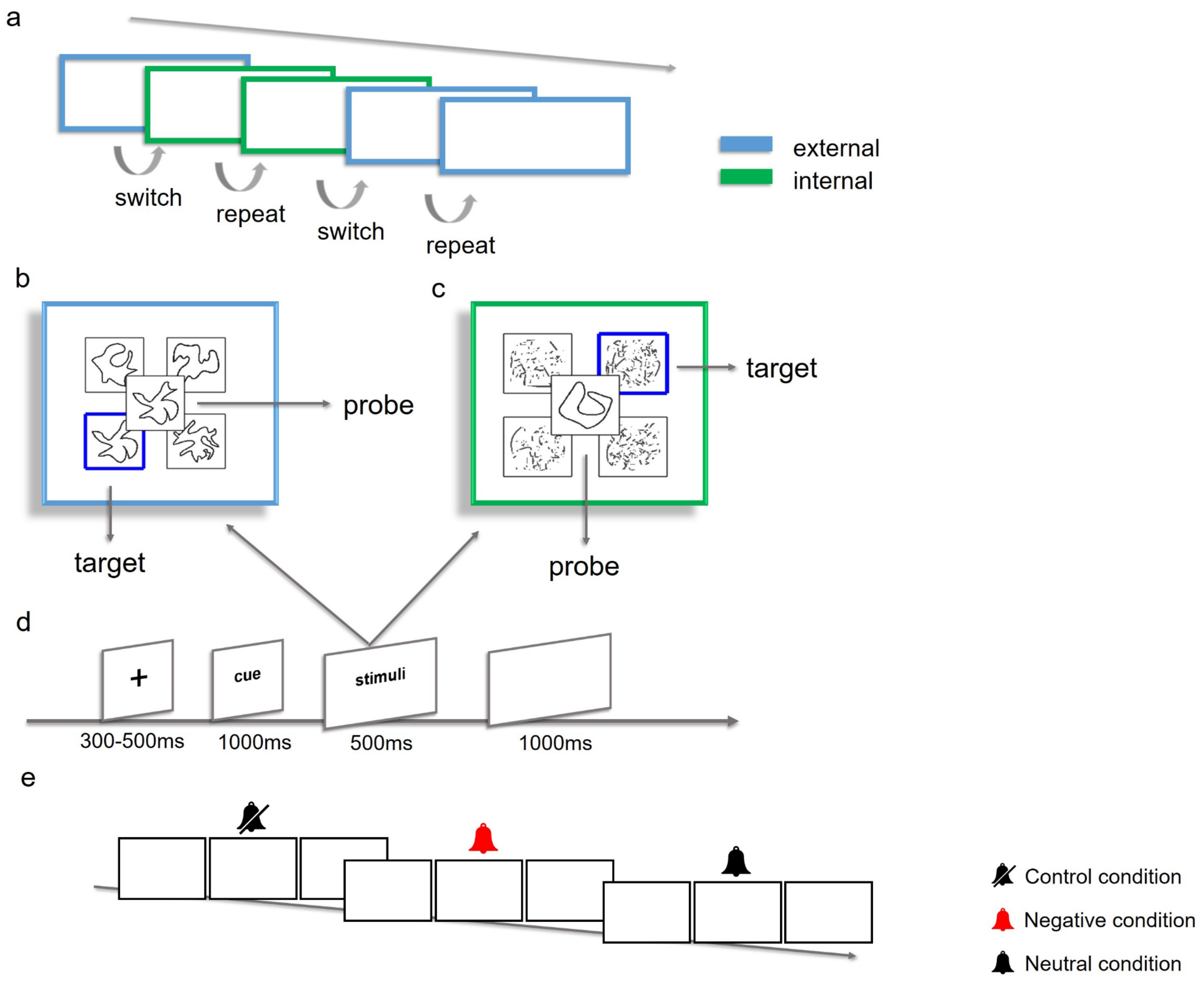

Fig. 1 Procedure

appeared after each trial during the practice block only. For each condition (i.e., control, neutral, negative; see below for information on their differences), three blocks were shown in succession. Each trial started with a fixation cross, presented with a jittered duration of 300–500 ms, before a 1000 ms (visual) cue appeared, either ‘E’ for external or ‘I’ for internal, to inform the participants about which Attention Type to use to complete the upcoming trial. Following this cue, the stimulus (i.e. the probe along with four peripheral figures, or scrambled figures in case of internal attention) was shown for 500ms, before placeholders were shown for 1000ms. All five stimuli had the same size of 2.646 cm × 2.646 cm, resulting in a size of 6.35 cm × 6.35 cm for the full visual display. Participants needed to respond within this 1500ms time limit (see Fig. 1d). Participants answered with their right index and middle fingers using the keys ‘g’ and ‘h’ of the keyboard. For half of them, ‘g’ indicated “match” whereas ‘h’ indicated “non-match”, while for the other half, the reverse mapping was used. After each block in the test phase, participants received general feedback about their (mean) accuracy.

(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 internal, and switch external. (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). 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. The order of the three conditions was counterbalanced across participants.

Throughout the whole test phase, participants wore insert earphones (3 M E-A-RTONE-3 A, 10 Ω) through which a specific sound could be played (see Fig. 1e). For the negative condition, the sound was a white noise burst (100dB, 50ms duration), as used in previous startle probe studies to increase state anxiety (i.e., arousal) and more specifically, induce hypervigilance (Grillon, 2008; Rossi & Pourtois, 2014). For the neutral condition, the sound was a low-volume, non-threatening sine wave (46dB, 200ms duration), corresponding to a safe condition. Their intensities and acoustic properties were verified with an artificial ear (GRAS 43AG-S2, Ear and Cheek Simulator with Kemar Pinna). Both sounds were played three times each at the beginning of the test phase as examples, and participants were reminded about which sound would be played during the following block before they started. In the neutral and negative conditions, the corresponding sound could appear at any random point within the block. There were 4 to 6 presentations of it during each block with randomly varying intervals between them (i.e., 15–20 trials). Hence, sound delivery was unpredictable. However, the sound was never played during instructions or feedback, and no sound was played during the control condition.

Levels of state anxiety were measured four times during the test phase: the first time before its start (i.e. baseline, which happened before sound examples) and then once after each condition. The state version of the State-Trait Anxiety Inventory (STAI-Y1) was administered to the participants to measure levels of state anxiety (Spielberger, 1983; Van der Ploeg & Defares, 1980), and the order of the 20 items composing it was systematically varied across these four measurements. Besides the STAI, participants were also asked to rate twice how much they (dis)liked the sound: once after the neutral condition and once after the negative condition. For this, we used a visual analog scale (VAS) ranging from 1 (very unpleasant) to 100 (very pleasant).

During the whole experiment, eye blinks and SCR were measured continuously using a Biosemi active two system (http://www.biosemi.com*)*. Signals were referenced online to the CMS–DRL and digitized at 512 Hz. Eye blinks were monitored through two electrodes attached above and below the left eye, while the SCR was collected through two bipolar electrodes applied to the index and middle fingers of the left hand[2]. Participants were instructed to comfortably lay their left forearm on the table in front of them and asked to keep it still while performing the task. All participants reported feeling more comfortable using their right hand to perform the task. Accordingly, they all used their right hand to carry out the task as well as fill out the ratings.

Data pre-processing and analysis

Data analyses were carried out with R (R Core Team, 2023; RStudio Team, 2023.06.0) and JASP (JASP Team, 2023, Version 0.17.1). For the STAI, we first subtracted the baseline score from each of the three conditions. These difference scores were analyzed by means of a Bayesian repeated measures analysis of variance (Bayesian RM ANOVA) with Emotion (3 levels: control, negative, neutral) as the main within-subject factor. A Bayesian paired-sample t-test was used to compare sound ratings between the neutral and the negative conditions. For the task data (i.e. accuracy and RTs for correct responses), all practice and training trials, as well as the first two trials of each block, but also the trials during which the sound was played, were removed. For RTs, error trials and trials following them were also removed. Task data were analyzed by means of a 2 (Switch Type: repeat, switch) × 2 (Attention Type: external, internal) × 3 (Emotion: control, neutral, negative) Bayesian RM ANOVA, and Bayesian paired-sample t-tests for pairwise post-hoc comparisons (as there are no post-hoc tests for interaction of Bayesian RM ANOVA in JASP, see Wagenmakers et al., 2018) to assess the evidence for or against our hypothesis.

Ledalab, which is a Matlab-based software for the analysis of skin conductance data (http://www.ledalab.de), was used to pre-process the data and to separate tonic (skin conductance level, SCL) from phasic (SCR) effects. A 5 Hz low-pass filter was applied to the data, which were all down-sampled to 32 Hz to speed up data processing. Previous studies suggested that this sampling frequency (i.e., 32 Hz) is adequate to analyze physiological signals (IMotions, 2017; Luharuka et al., 2003). Data were smoothed with a gauss window width of 8 samples (Benedek & Kaernbach, 2010). Continuous Decomposition Analysis, which is based on Standard Deconvolution, was applied to extract tonic and phasic effects. Continuous Decomposition Analysis deconvolves skin conductance data with the general response shape, which results in a large increase of temporal precision. This method implements a zero-baseline (baseline correction method to create a consistent baseline) and is suited to estimate closely succeeding responses occurring in a rapid sequence (Benedek & Kaernbach, 2010; Kuhn et al., 2022). For each sound, the corresponding event-related SCR was extracted using an epoch of 6 s (i.e. 1s before and 5s after the sound), and an SCR amplitude threshold of 0.05 µS (microsiemens) was used, which was previously suggested as the minimum amplitude criterion (Benedek & Kaernbach, 2010). The SCR was compared

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[2] 7 out of 49 participants were left-handed, however, they all reported they felt comfortable to use their right hand to perform the task. Therefore, the SCR was recorded from the left hand for all participants.

using a Bayesian paired-sample t-test between the two main conditions (negative vs. neutral). For each condition separately, we also extracted the SCL and compared it between them using a Bayesian RM ANOVA with Emotion (control, neutral, negative) as the main factor. For the eye blinks, we used BLINKER, which is a Matlab-based plugin for EEGLAB (Kleifges et al., 2017). Each candidate signal in BLINKER is band-passed filtered in the 1–20 Hz interval prior to blink detection. The BLINKER algorithm then determines the intervals during which the signal is greater than 1.5 standard deviations above the overall signal mean, which are marked as potential blinks. Only potential blinks that were longer than 50 ms and at least 50 ms apart were retained for further analyses. These values were analyzed using a Bayesian RM ANOVA with Emotion (control, neutral, negative) as the main within-subject factor. For all data analyses (STAI, SCR, SCL, and eye blinks), we detected and replaced outliers using a median absolute deviation criterion (Leys et al., 2013). We followed the criteria suggested by Jeffreys (1998) to interpret the Bayes factor (BF), i.e. $BF < 1/10$ ($BF > 10$) indicates strong evidence supporting H_0 (H_1), $1/10 < BF < 1/3$ ($3 < BF < 10$) indicates moderate evidence supporting H_0 (H_1), $1/3 < BF < 1$ ($1 < BF < 3$) indicates anecdotal evidence supporting H_0 (H_1).

Diffusion model analysis

To gain insight into the modulatory effects of hypervigilance on attentional balance, we also analyzed the accuracy and RT data using a hierarchical drift diffusion model (HDDM) with Python 3.7 (Van Rossum & Drake, 2009) and HDDM 0.9.9 (Wiecki et al., 2013). Following previous recommendations (Karayanidis et al., 2009; Schmitz & Krämer, 2023; Schmitz & Voss, 2011, 2014), the starting point (z) was 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, while the other parameters including drift rate (v) and non-decision time (t0) were allowed to vary freely across Switch Type, Attention Type, and Emotion. Before model estimation, all practice and training trials, as well as the first two trials of each block, and trials that followed errors were removed (following the suggestion of Schmitz & Voss, 2011, 2014). Moreover, 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).

Table 1 Model details and comparisons

model	Parameter setting	DIC
Model 1	a : S v : S×A×E t0 : S×A×E st0	-23029.004
Model 2	a : S v : S×A×E t0 : S×A×E	-19119.717
Model 3	a v : S×A×E t0 : S×A×E st0	-23049.823
Model 4	a v : S×A×E t0 : S×A×E	-19172.816

Note S – Switch Type, A – Attention Type, E – Emotion. a: boundary separation; v: drift rate; t0: non-decision time; st0: the inter-trial variability of non-decision time

Since we had no specific hypothesis regarding response caution, boundary separation (a) was set as suggested in previous studies: it was only allowed to vary with Switch Type or was fixed across all conditions (Imburgio & Orr, 2021; Karayanidis et al., 2009; Schmitz & Voss, 2011). Furthermore, it has been pointed out that variability of non-decision time (st0) always exists during the decision-making process, and adding it to the model can improve model fitting. Accordingly, we also considered models with and without this parameter (Ratcliff et al., 2006; Ratcliff & Tuerlinckx, 2002). Because accuracy in the current experiment was overall high (and similar to previous studies, see Verschooren et al., 2019) and there was no evidence supporting either slow or impulsive errors, we did not include inter-trial variability of starting point (sz) and drift rate (sv) as they indicate unusual errors (Boehm et al., 2018; Ratcliff & Tuerlinckx, 2002; Voss et al., 2013). From these choices, four models were estimated for model comparison (see Table 1).

The best-fitting model was chosen based on the Deviance Information Criterion (DIC); the model with the smallest DIC was considered the best one. Moreover, a DIC difference of 10 is considered strong evidence for model comparison (Kass & Raftery, 1995). Model convergence was confirmed by visual inspection and Gelman-Rubin statistics (Gelman & Rubin, 1992) for each of the models. Furthermore, we confirmed that the best-fitting model captured the behavioral data well by conducting posterior predictive checks, which were made through visualization and mean square error (MSE) between two datasets, where the smaller the MSE is, the better the model fit is (reflecting a smaller difference between simulated data and real data; Hu et al., 2020). Furthermore, R-hat was calculated with 4 chains, each with 5000 iterations and 1000 burn-in samples. We examined and reported the proportion 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 (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. In the current study, we considered the proportion which is below 0.05 (above 0.95) as strong evidence revealing difference, while the proportion of 0.09 or 0.081 (above 0.05 but below 0.1) indicates sufficient but weak evidence supporting a difference between conditions.

Results

Manipulation checks

Self-report

There was strong evidence supporting the difference in sound pleasantness rating between negative and neutral conditions. Participants rated the negative sound as less pleasant than the neutral one, showing they disliked the aversive sound at the subjective level, $BF_{10} = 3.943 \times 10^{+15}$ ($M_{negative}$=16.641, $M_{neutral}$=63.631, see Fig. 2a). Regarding the STAI, we did not find evidence supporting the effect of Emotion, implying that levels of state anxiety were similar between conditions, BF_M=0.928, model averaged $R^2 = 0.456$ (see Fig. 2b).

SCL, SCR, and eye blinks

Compared to the neutral condition, strong evidence supported a larger SCR in the negative condition compared to the neutral condition, $BF_{10} = 39076.157$ ($M_{negative}$=0.025, $M_{neutral}$=0.012, see Fig. 3a). Regarding the eye blinks, there was strong evidence for an effect of Emotion, BF_M = 3976.709 (model averaged $R^2 = 0.255$). Eye blinks were higher in the negative than in the neutral condition ($BF_{10,\ U}$=927.267). Hence, tension, arousal or even stress likely increased in the negative compared to the neutral condition, thereby providing an indirect confirmation of a distinct negative state elicited in the former compared to the latter condition. However, because they did not differ between the negative and the control conditions ($BF_{10,\ U}$=0.157) and moreover they were significantly lower for the neutral than the control condition ($BF_{10,\ U}$=648.860) (see Fig. 3c), these results suggest that eye blinks selectively decreased in the neutral condition compared to the two other ones. Hence, some caution is needed in their interpretation because they might also reveal a different attentional state in the neutral condition compared to the two other conditions, which was not expected a priori. Regarding the SCL, it was also comparable for the three conditions (BF_M = 0.093, model averaged $R^2 = 0.919$, see Fig. 3b), suggesting that (tonic) physiological arousal was similar for them.

Task performance

Accuracy and RTs

The Bayesian RM ANOVA run on the accuracy data revealed moderate evidence supporting the best model containing the main effects of Switch Type and Attention Type (BF_M=4.721, model averaged $R^2 = 0.610$). Post-hoc tests revealed strong evidence supporting the main effect of Attention Type. Participants were more accurate for external than internal trials ($BF_{10,\ U} = = 2.712 \times 10^{+10}$; see Supplementary Table S1 for the descriptive statistics).

Regarding the RTs, strong evidence supported the most complex model including all the main effects and

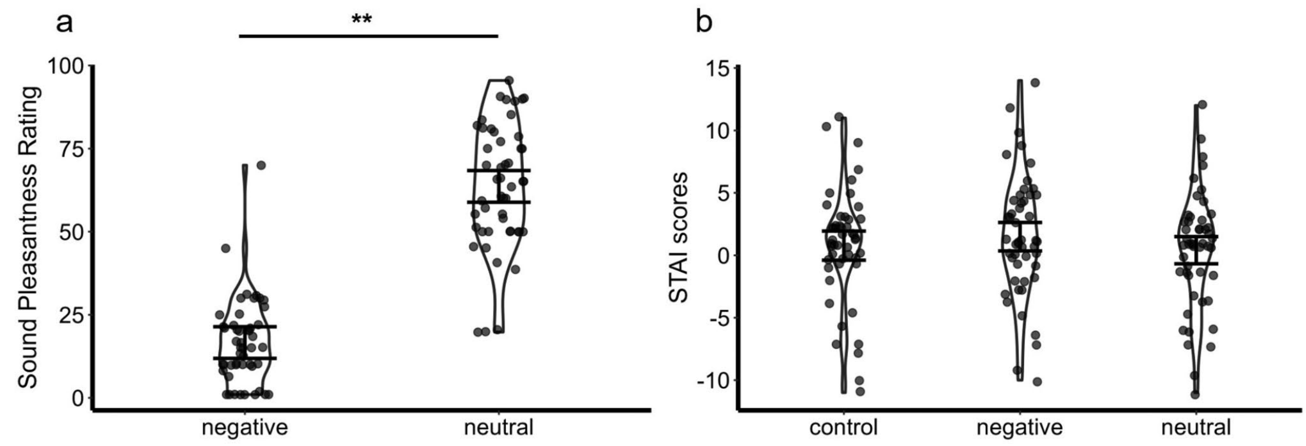

Fig. 2 Self-report results. **a**. Levels of sound pleasantness ratings. The scale ranged from 1 (very unpleasant) to 100 (very pleasant). **b**. Levels of state anxiety (STAI) for each condition separately. These levels were baseline-corrected. Note: The error bars show mean ± within-subject 95% confidence interval (wsci). '*' represents weak or moderate evidence supporting the difference between two conditions; '**' represents strong evidence

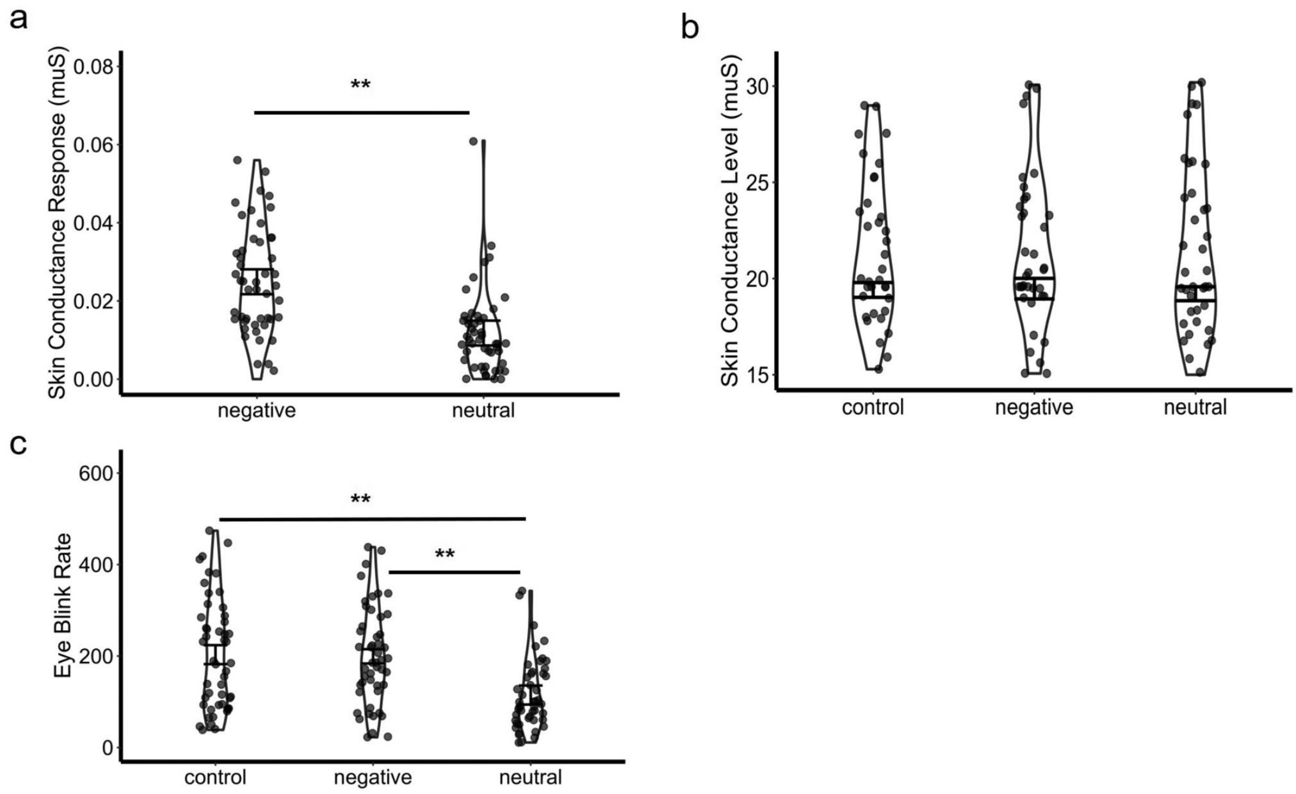

Fig. 3 Physiological results. **a**. SCR for the negative and neutral conditions; **b**. SCL for each condition separately; **c**. Eye blink rate for each condition separately. Note: The error bars show mean ± wsci. ‘*’ represents weak or moderate evidence supporting the difference between two conditions; ‘**’ represents strong evidence

interactions between Switch Type, Attention Type, and Emotion[3], BF_M=10.166, model averaged $R^2 = 0.802$. Participants were slower on switch than repeat trials ($BF_{10,\ U}$=$1.402 \times 10^{+11}$), on internal compared to external trials ($BF_{10,\ U}$=$2.014 \times 10^{+43}$), and in the neutral than the control ($BF_{10,\ U}$=56178.778) and negative conditions ($BF_{10,\ U}$=73.690). Importantly, the three-way interaction between Switch Type, Attention Type, and Emotion was supported by strong evidence, BF_{incl} = 10.166. To explore this interaction further, we ran three Bayesian RM ANOVAs, for each condition separately. In both the control and neutral conditions, the interaction between Switch Type and Attention Type was significant (control: BF_{incl} = 1375.899; neutral: BF_{incl} = 12.404). While participants were slower for switch than repeat internal trials (control: $BF_{10} = 10084.083$; neutral: $BF_{10} = 5985.585$), there was no difference between repeat and switch for external trials in the control condition (replicating Verschooren et al., 2019), and this difference was less in the neutral condition (control: $BF_{10} = 0.297$; neutral: $BF_{10} = 8.009$). In comparison, in the negative condition, no evidence supported the two-way interaction between Switch Type and Attention Type (BF_{incl} = 0.739). Participants were not slower for switch than repeat trials for both modalities (external: $BF_{10} = 2.811$; internal: $BF_{10} = 1.375$) (see Fig. 4a).

To aid interpretation, we then calculated the switch cost (i.e. switch minus repeat trials) for each condition separately and analyzed them in a supplementary RM Bayesian ANOVA. We found weak evidence supporting the model including the interaction between Attention Type and Emotion, BF_M=2.679, model averaged $R^2 = 0.248$. Post-hoc comparisons showed a larger switch cost for internal than external trials ($BF_{10,\ U}$=21.512). Moreover, asymmetric switch costs were expressed in the control and neutral conditions (control: $BF_{10} = 58.428$; neutral: $BF_{10} = 2.176$,); while it was not found in the negative condition ($BF_{10} = 0.160$) (see Fig. 4b). Moreover, participants also had a smaller switch cost for internal trials in the negative than the control condition (negative-control: $BF_{10} = 5.727$; neutral-negative: $BF_{10} = 0.679$; neutral-control: $BF_{10} = 0.275$). In comparison, no significant difference on external trials between conditions was found (negative-control: $BF_{10} = 0.318$; neutral-negative: $BF_{10} = 0.155$; neutral-control: $BF_{10} = 0.463$).

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[3] This model was the second best model during model comparison, which had a comparable BF_M compared to the best model (BF_M=12.397). We chose the second best model because we were mostly interested in the three-way interaction between Switch Type, Attention Type, and Emotion.

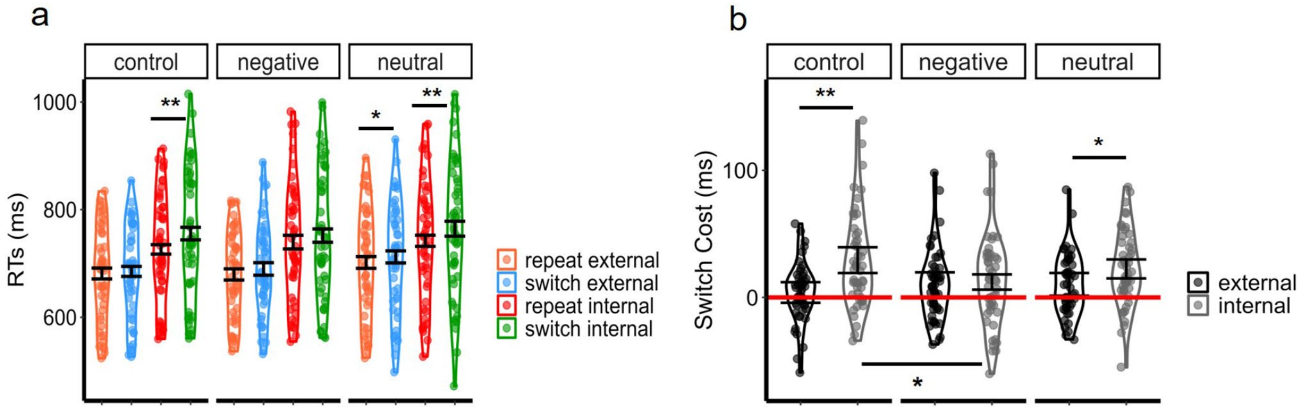

Fig. 4 Behavioral results (RTs). **a**. RTs for the different conditions, separately; **b**. Switch cost (in RTs) for the different conditions, separately. Note: The error bars show mean ± wsci. '*' represents weak or moderate evidence supporting the difference between two conditions; '**' represents strong evidence

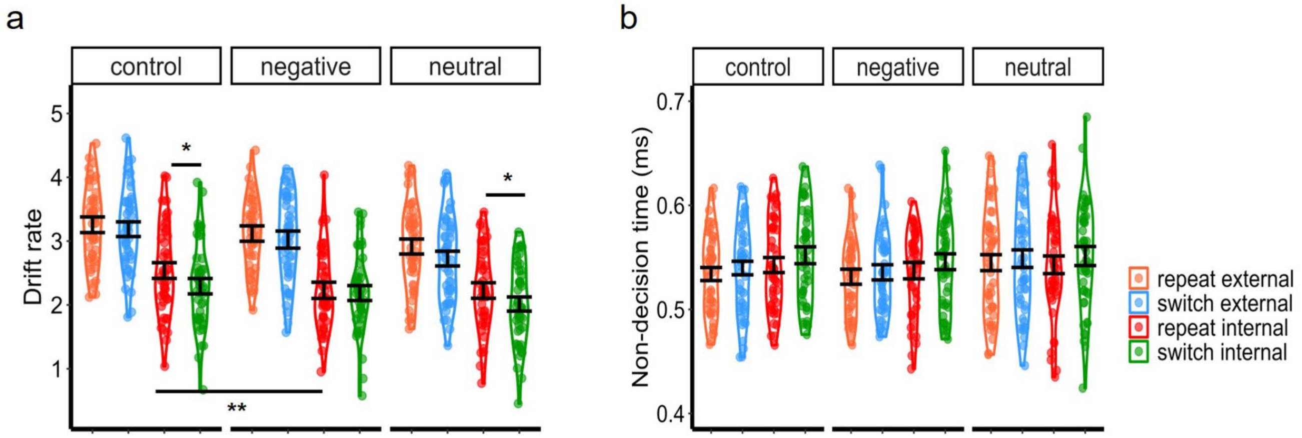

Fig. 5 HDDM results. **a**. Drift rate (v) for the different conditions separately; **b**. Non-decision time (t0). Note: The error bars show mean ± wsci. '*' represents weak or moderate evidence supporting the difference between two conditions; '**' represents strong evidence

DDM

The model with drift rate (v) and non-decision time (t0) varying with the three-way interaction between Switch Type, Attention Type, and Emotion (Model 3) yielded the best fit (see Table 1, where Model 3 shows the smallest DIC)[4]. We confirmed that this model had good convergence (see Supplementary Figure S2), and the posterior predictive checks showed that it captured the data well (MSE = 0.022, see the visualization in Supplementary Figure S3-S6). Last, the R-hats for all parameters were close to 1 and not larger than 1.01 (M = 1.00016, SD = 0.000274), which also indicated good convergence (Ulrichsen et al., 2020) (see Supplementary Table S2 for descriptive statistics).

As expected, we found similar asymmetric switch costs in the control and neutral conditions on drift rate (v). In these two conditions, there was weak evidence supporting a lower drift rate (v) for switch internal compared to repeat internal trials, while there was no evidence for this difference on external trials (control: $p_{(SI>RI)}$[5] $= 0.081$, $p_{(SE>RE)} = 0.361$; neutral: $p_{(SI>RI)} = 0.090$, $p_{(SE>RE)} = 0.149$). This asymmetry was not found in the negative condition, where there was no difference between switch and repeat trials for none of the two attention types (negative: $p_{(SI>RI)} = 0.415$, $p_{(SE>RE)} = 0.303$). Moreover, we found that participants had a lower drift rate (v) on repeat-internal trials in the negative compared to the control condition, while no difference was found on switch internal, repeat external, or switch external trials between conditions (repeat-internal: $p_{(\text{negative}>\text{control})} = 0.033$). Regarding non-decision time (t0), no difference was found (See Fig. 5 and Supplementary Table S3 for details).

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[4] We also examined boundary separation (a) with an extra model estimation (see Table S4 in Supplementary Materials).

[5] S – switch, R – repeat; E – external, I – internal.

Discussion

To investigate the influence of hypervigilance on attentional balance, we used the SAT in healthy adult participants and compared behavioral performance between three conditions: no sound, safe sound, or aversive sound. Manipulation checks confirmed that we likely induced hypervigilance when the SAT was performed and an aversive sound was played. At the subjective level, participants disliked the aversive sound more than the safe sound. Moreover, the SCR increased in response to the aversive sound, compared to the safe sound. Importantly, we found that hypervigilance influenced attentional balance, in a way that was consistent with our hypothesis. By reducing the shielding of internal attention, hypervigilance reduced the switch cost asymmetry typically found between internal and external attention. In addition, our HDDM results revealed that a change of the drift rate (v), as opposed to the non-decision time (t0), was underlying this effect driven by hypervigilance on attentional balance during the SAT. Hereafter we discuss the implications of these new results in greater detail.

A closer look at the manipulation checks confirms that hypervigilance, as opposed to undefined state anxiety, was probably elicited in the negative condition (Grillon, 2008; Rollman, 2009). In the negative condition, the SCR was substantially larger compared to the neutral condition. Moreover, the aversiveness of the sound in the negative condition was also confirmed by the sound ratings. Hence, compared to the neutral sound, the aversive one increased physiological arousal transiently (but not tonically) and at the subjective level, participants disliked the latter one more than the former one. In comparison, state anxiety, as measured by the STAI (as well as SCL indirectly), was comparable between the three conditions. This lack of effect at the STAI level was not surprising because of its poor discriminant validity; for example, it shows only weak correlations with negative affect resulting from electric shock manipulations (Bijsterbosch et al., 2019). Hence, it probably measures a general negative affect component (Bieling et al., 1998; Rocher & Pickering, 2022) and it is probably not appropriate to capture more specific negative affective states, such as hypervigilance (or anxious arousal) in our study. As mentioned here above, a similar interpretation could be drawn when considering eye blinks for which a decrease in the neutral condition, as opposed to an increase in the negative one is observed. Accordingly, the aversive sound increased physiological arousal and participants disliked it, yet this manipulation did not simply induce state anxiety based on the STAI, SCL, and eye blinks. The SCL is suited to capture long-lasting fluctuations of the ANS which can arise due to specific (negative) emotional states, bouts, or specific situational demands, while the SCR tracks phasic changes of the ANS elicited by external negative or threatening stimuli (Boucsein, 2012). Combined, our findings for the SCL and SCR indirectly confirm that the aversive sound we used elicited a phasic increase of arousal as opposed to a sustained autonomic nervous system (ANS) change. Hence, based on the manipulation checks where both subjective ratings and peripheral physiological data were considered, it can be concluded that a state of hypervigilance, or perhaps enhanced autonomic arousal bound to the aversive sound presentation, was likely elicited in the negative compared to the neutral and control conditions.

Interestingly, when participants were in this state of hypervigilance, we found a reduced switch cost asymmetry compared to the neutral and control conditions. The DDM results revealed that this reduced asymmetry was mostly caused by a lower drift rate (v) for repeat internal trials in the former condition. In comparison, hypervigilance did not influence switch internal trials, nor external trials (both repeat and switch). Accordingly, our results do not show that hypervigilance creates a general boost or bias toward external attention (e.g. repeat external) and/or it jeopardizes internal attention (e.g., switch internal). Instead, they show that hypervigilance selectively impairs the shielding of internal attention (i.e., it undermines the benefit found for repeat internal trials in the control and neutral conditions). Several studies already reported that hypervigilance or sustained anxiety could increase alertness and facilitate external attention even for neutral stimuli, including attentional orienting (Max et al., 2015), selective attention (Chajut & Algom, 2003; Wieser et al., 2016), visual detection (Minnick et al., 2020), or early visual processing (Phelps et al., 2006). However, these studies did not explore attentional balance, as defined by the ability to switch between internal and external attention. When attentional balance is conceived according to this framework, as done in our study, hypervigilance seems to impair the shielding of internal attention selectively, and this effect likely stems from an automatic or uncontrolled orienting of attention towards external stimuli, which can be detrimental to performance when internal attention has to be used on consecutive trials (i.e., repeat internal trials). Although staying with internal attention on (two) consecutive trials is beneficial to behavioral performance in a neutral emotional state, hypervigilance likely impedes this gain because the need or urge to deploy attention "automatically" towards the external domain is high, with the aim to monitor and scan this environment (where a threatening stimulus, namely an aversive sound, may be delivered at an unexpected time point). As mentioned above, according to the associative interference hypothesis, the asymmetric switch cost is thought to result from the different shielding efficiency between internal and external attention. Our results show that this very mechanism is likely altered by hypervigilance, resulting in turn in an inefficient shielding of internal attention because interference from external attention is enhanced.

Because of this selective impairment on repeat internal trials, the switch cost for internal trials turned out to be reduced under hypervigilance compared to the neutral and control conditions, even though participants were generally slower to process internal than external trials (as was expected based on Verschooren et al., 2020). Hence and surprisingly at first sight, hypervigilance appears to create a more symmetrical and balanced control of attention when it has to be allocated to external and internal information concurrently, eventually suggesting that this negative affective state might actually decrease the switch cost. This interpretation is in stark contrast with the Attentional Control Theory (ACT, Eysenck et al., 2007) according to which anxiety impairs cognitive and attentional flexibility (Derakshan et al., 2009; Gustavson et al., 2017; Hartanto & Yang, 2022). However, an important nuance is that, in the ACT, attentional control directly relates to specific executive functions, including shifting, inhibition, and updating (Eysenck et al., 2007), while here, we focused on the peculiar ability to switch dynamically and on a trial by trial basis between external and internal attention (i.e. attentional balance). Moreover, ACT also focuses primarily on anxiety whereas here we assessed effects of hypervigilance on attentional balance. As a caveat, we cannot conclude however based on the current findings that hypervigilance facilitated attentional balance because it did not improve performance on switch trials; an effect which would be expected if this was the case (Derakshan et al., 2009). Hence, some caution is needed in the interpretation of these results and additional studies using the SAT are needed to assess if and how state anxiety (e.g. worry or rumination) might influence attentional balance, perhaps in a dissociable way compared to hypervigilance (Shackman et al., 2016; Vytal et al., 2012).

Another noteworthy finding resulting from our study is that hypervigilance mostly influenced the drift rate (v) of repeat internal trials during the SAT, selectively, while leaving the non-decision time (t0) unaffected. Drift rate (v) is the speed with which information about the stimulus accumulates to guide the decision-making process (Voss et al., 2004); while non-decision time (t0) represents the time of encoding and decision execution (i.e. motor activation, e.g. key-pressing) and it mostly captures the non-decision process of decision-making (Weindel et al., 2021). According to previous DDM studies, these two different parameters can be used to decompose the switching process into reconfiguration (which is mostly cue-related and revealed by non-decision time (t0) and proactive interference (which relates to associative interference, and which is target-related and reflected by drift rate (v) (Karayanidis et al., 2009; Schmitz & Voss, 2011, 2014). In the light of this dissociation, we can therefore assume that hypervigilance mostly influenced associative interference; an interpretation which is in line with our discussion above. On the other hand, our results for the non-decision time might suggest that participants had sufficient time to complete task reconfiguration before target onset. The duration for the cue (i.e. 1000ms) was relatively long compared to previous task-switching studies (Imburgio & Orr, 2021; Schmitz & Voss, 2011, 2014), which likely provided the participants with enough time to reconfigure for all trial types, potentially canceling out the modulation of Switch Type, Attention Type, or Emotion on this specific parameter. Alternatively, we cannot rule out the possibility that reconfiguration was incomplete and that this process varied across conditions, even if non-decision time did not reveal that. Because non-decision time (t0) may not be unequivocal evidence of task-set reconfiguration, for which both encoding and motor/decision processes are involved (Weindel et al., 2022), caution is needed when interpreting the lack of non-decision time (t0) effects in our study. By combining the SAT with other methods, including electroencephalography (EEG), more conclusive evidence regarding reconfiguration triggered by the cue with this task could be obtained. Likewise, it appears important in future behavioral studies based on the SAT to manipulate the cue-target interval to assess its impact on the (asymmetric) switch cost measured with RTs, but also the drift rate (v) as well as non-decision time (t0).

Last but not least, we also found an unexpected effect in the neutral condition, where the RTs were overall slower, accompanied by slower drift rates (v) compared to the control and negative conditions (see Supplementary Table S3). Compared to the control condition devoid of sound, sound delivery as such could influence attentional control, yet this influence was clearly different if the sound was aversive (i.e., in the negative condition where hypervigilance was induced). Tentatively, slower RTs in the neutral condition could suggest that the sound, albeit being safe, yielded some distraction. In agreement with this interpretation, in this condition, participants also blinked the least, which might suggest a change in their cognitive control ability, perhaps related to dopamine neurotransmission even (Eckstein et al., 2017; Jongkees & Colzato, 2016). Importantly, whereas the safe sound in the neutral condition might decrease attentional control, the aversive one in the negative condition impinged on the shielding of internal attention, selectively. If we bring these two results together, one can also explain why hypervigilance did not simply enhance external attention because the unspecific distraction effect created by the sound (in the neutral condition) was likely compensated by a selective gain for external attention in this negative state.

Some limitations warrant comment. First, we believe our findings need to be replicated with other tasks or in different contexts before their robustness or generalization could be assessed. Moreover, although we found a change in the SCR as a function of the aversive sound manipulation, we lack more direct evidence confirming that hypervigilance was truly elicited. However, given the strong correlation found in the literature between physiological arousal and hypervigilance, we are inclined to believe that hypervigilance was likely elicited in the negative condition. To address this caveat, in future studies on this topic, different negative stimuli (than the aversive sound) could be used (for induction) in combination with additional physiological measures (such as the heart rate and/or the startle blink reflex) in order to establish the elicitation of hypervigilance in the negative condition. Another limitation pertains to the lack of a suited or validated scale or inventory at the subjective level to measure hypervigilance, as opposed to state anxiety, for which the STAI is often used. Furthermore, caution is needed when using difference score to quantify the switch cost (i.e. switch minus repeat trials, see Fig. 4b) and interpreting its asymmetry between external and internal attention. Repeat trials are treated as a stable baseline when calculating the switch cost, however, when performance for them corresponds to a ceiling effect (in one condition), the switch cost calculated based on the difference score might be artificially inflated (in that condition). Therefore, we recommend using the performance (RTs) for each condition separately for the main statistical analyses (see Fig. 4a) and supplementing them with the difference scores in auxiliary ones (Fig. 4b). Last, we believe that in order to formally corroborate the assumption of a deficit of internal attention's shielding caused by hypervigilance, additional behavioral and modeling studies are needed, where the SAT could be amended. For example, it would be extremely valuable to assess behavioral performance with the SAT under hypervigilance when a regular or rhythmic trial order is used (i.e. I-I-I-I-E-E-E-E-I-I-I-I…where I denotes internal and E external attention). Presumably, hypervigilance could impair behavioral performance during the repetitions of internal attention trials, and this cost might even increase or vary depending on their actual number.

In summary, the results of this study based on the SAT show that hypervigilance creates a specific modulatory effect on attentional balance, namely it jeopardizes the shielding of internal attention. As a result, hypervigilance eventually leads to a seemingly more balanced and less asymmetric control of attention between external and internal information when these two repertoires or domains compete with one another for selection and processing. Because the drift rate mostly captured this change of attentional balance as a function of hypervigilance, these results indirectly suggest that associative interference might be responsible for it.

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Data availability The behavioral data are available in the Open Science Framework (DOI: 10.17605/OSF.IO/59Q72).

Declarations

Competing interests The authors declare no competing interests.

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