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Brain and behavioural dynamics of auditory distraction

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Contents

1. General introduction

The environment abounds with sensory information. For instance, having a conversation with a friend in a café, human listeners are surrounded by all the background noises such as the sizzling from the coffee machine or the chitchat from the strangers at the next table. The mental faculty to prioritize the task-relevant targets (e.g., a friend's voice) while ignoring the task-irrelevant distractors (e.g., chitchat from others) is referred to as selective attention (Desimone & Duncan, 1995). Given limited resources in the human brain, selective attention is crucial for successful performance in goal-directed tasks (e.g., successful communication with a friend).

The human brain is dynamic with moment-to-moment changes in its state of excitability (Bishop, 1932; M. X. Cohen, 2017). The oscillatory nature of the human brain is said to be instrumental to the selection of task-relevant targets. Research has suggested that the processing of task-irrelevant distractors may not be collateral but rather an independent process from the selection of targets (Gundlach et al., 2022; Wöstmann et al., 2019). How the dynamics of the brain correspond to the proneness to distractors, however, has been largely neglected in the literature. This thesis aims at filling this gap by examining how the endogenous (i.e., neural oscillations) or the exogenous (temporal or statistical regularities from the environment) dynamics explain the behavioural dynamics of the proneness to distraction.

1.1 Selective attention

The café scenario describes the "cocktail party" phenomenon, which set a milestone in the study of selective attention (Cherry, 1953). Broadbent's filter theory of attention (1958) posited that selective attention functions as a selective filter, where the task-irrelevant information is filtered out based on basic physical features. Subsequently, different theories of the attentional filter have sprung regarding at which stage the distractors are filtered out (e.g., Deutsch & Deutsch, 1963; Treisman, 1960; Yantis & Johnston, 1990). This thesis adopts the view that selective attention consists of multiple loci of filters at different levels, and the task-irrelevant distractors may be filtered out at any given stage of processing. In the following, I will briefly outline the early versus late selection debate for a comprehensive view of the theories of the attentional filter.

1.1.1 Hierarchy of the attentional filter

The stage at which distractors are filtered out has long been debated in attentional filtering research. The early selection view (Broadbent, 1958) holds that only basic properties of the unattended sounds, such as location (e.g., Hirsh, 1950; Poulton, 1953) and pitch (e.g., Cherry, 1953; Egan et al., 1954; Spieth et al., 1954), are processed while the higher-order properties, such as the semantic features, are entirely filtered out. Studies examining attentional filtering usually employed a dichotic listening task where participants were instructed to attend to one ear and ignore the other. In the seminal paper (Cherry, 1953), participants were able to identify the gender of the talker and whether the auditory input was a speech from the ignored ear. However, participants failed to report features such as the language of the ignored speech. Subsequent evidence in favour of the early selection view showed a poor memory recognition of the to-be-ignored items (Moray, 1959).

The late selection view, on the other hand, posited that both targets and distractors are processed perceptually in parallel, and the selection process only takes place afterwards during the post-perceptual processes (Duncan, 1980). This view was based on empirical studies which showed inconsistency with the early selection view (e.g., Gray & Wedderburn, 1960; Peters, 1954). For example, semantically similar distractors interfered with the attended targets more than semantically dissimilar distractors (Peters, 1954), demonstrating that the ignored distractors were processed on the semantic level at least to a certain degree. In Gray & Wedderburn (1960), instead of reporting the words and syllables from the attended side, participants reported a meaningful sentence that was interspersed between attended and ignored sequences. These studies suggest that the task-irrelevant stimuli are processed at least to some extent.

To accommodate both the empirical evidence supporting the early and the late selection views, Treisman (1960, 1964) proposed the attenuation model. According to Treisman (1960, 1964), instead of being completely filtered out, the task-irrelevant distractors are rather attenuated. Then, the distractors were filtered out based on the corresponding “threshold”. Thus, the selection of distractors may still be possible depending on how low the threshold is, which can be determined by factors such as the importance or familiarity of the input. For instance, one’s own name has a higher priority (Moray, 1959), and hence a lower threshold to pass through the attentional filter. Treisman’s theory modified the original theory of the attentional filter (Broadbent, 1958) by introducing flexibility in the filtering process.

Instead of siding with either early or late selection, the load theory of attention hypothesised that the locus of the attentional filter depends on the task demand, namely the perceptual load and cognitive load of the current task (Lavie, 1995, 2005; G. Murphy et al., 2016). Specifically, distractors are filtered at an early stage if the perceptual load in the task-relevant stimuli is sufficiently high. The perceptual load could be manipulated in different ways such as the number of items (e.g., Beck & Lavie, 2005; Lavie & De Fockert, 2003) or noise level (Gutteling et al., 2022). With high perceptual load, distractors are not processed and thereby do not interfere with the task-relevant selection process. On the other hand, with a low perceptual load, the human brain still has the capacity to process task-irrelevant distractors. Thus, in the low perceptual load condition, both the target and distractor can be processed perceptually. In such a case, the influence of the cognitive load would be evident. An increase in the working memory demand (e.g., the number of items held in working memory) would tax the cognitive control capacity, rendering it harder to suppress the interference of distractors. The distractor interference based on cognitive load is consistent with the late selection view where the post-perceptual process is engaged to filter out external distraction.

1.1.2 The components of distraction

Often in daily life, the relevant information is embedded in a multitude of irrelevant information. In these situations, human listeners need to both select the task-relevant target inputs (i.e., target selection) and suppress the task-irrelevant distractor inputs (i.e., distractor suppression) to achieve optimal goal-directed performance (Noonan et al., 2018). However, a search on the publications containing the search terms related to two constructs (target selection: "target enhancement" OR "target selection"; distractor suppression: "distractor suppression" OR "distractor inhibition" OR "distractor filtering" OR "noise suppression") reveals a disproportional focus in the current body of literature leaning towards target selection (Figure 1.1).

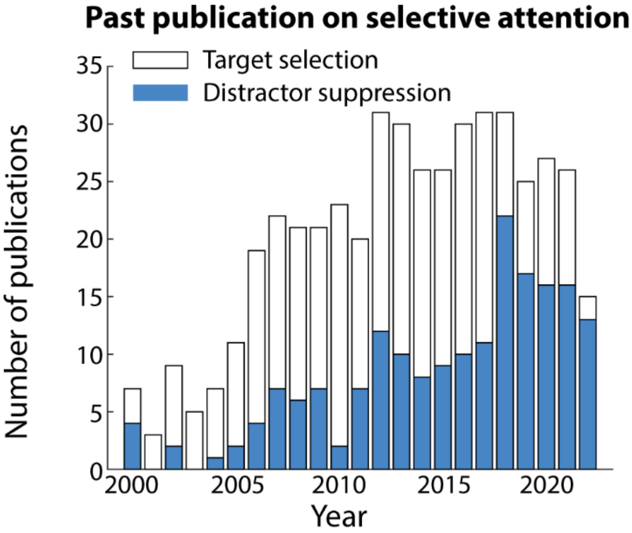

Figure 1.1. Number of publications with the search terms related to target selection (white) and distractor suppression (blue) over the past 35 years.

This thesis aims to provide evidence on the neglected side of the attentional filter:

the disruptive influence of external distractions. The final degree of distraction of the task-irrelevant information depends on 1) the listener's ability to suppress the anticipated distractor (i.e., distractor suppression), and 2) the listener's general proneness to distraction (i.e., distractibility). Several reviews have attempted to provide a theoretical framework of distraction as a backbone for empirical investigations (Geng, 2014; Noonan et al., 2018; Schneider et al., 2021). However, the taxonomy in the current distraction literature regarding the different components of distraction has not been well defined. To anchor this thesis in the current literature, I will here briefly review different components of distraction and provide the rationale for the use of terminology in this thesis. Of note, this section mainly focuses on distractor suppression and distractibility; other factors contributing to distraction, such as distractor strength and attentional capture, are not discussed here (for a review on attentional capture, see Luck et al., 2021).

First, there are different forms of distractor suppression. The selective suppression or inhibition of the task-irrelevant distractors can involve reactive or proactive mechanism (Geng, 2014). Reactive suppression refers to the inhibitory response to the distractor (Geng, 2014), which is particularly important when the distractor has the potency to capture attention (e.g., distractors with the salient feature). In Geng & DiQuattro (2010), when only the distractor was salient, participants were able to rapidly disengage from the processing of the salient distractor even when they made their first saccade towards the distractor. Distractor positivity (P_D), a neural index used to study post-stimulus reactive distractor suppression, was larger with a faster target detection (Gaspar & McDonald, 2014; Jannati et al., 2013). On the other hand, proactive suppression describes the preparatory inhibition of the upcoming distractor (Noonan et al., 2018; van Moorselaar & Slagter, 2020). Proactive suppression takes place when the distractors are anticipated. One major neural correlate of preparatory distractor inhibition is the alpha oscillatory power (Schneider et al., 2021). For instance, the posterior alpha power increased with anticipated distractors that were more similar to the to-be-remembered targets (Bonnefond & Jensen, 2012). Alpha oscillatory power was also lateralised in spatial attention tasks, with a contralateral decrease and ipsilateral increase in alpha power to the attended side (Haegens et al., 2011; Kerlin et al., 2010; Worden et al., 2000).

Within the proactive suppression mechanism, there has been a debate regarding whether, and if so, to what extent is distractor suppression active (Noonan et al., 2018; Schneider et al., 2021). Active suppression (or direct inhibition in Noonan et al., 2018) refers to distractor suppression independent of target selection, which was considered the flipside of target enhancement. Automatic suppression (or secondary inhibition in Noonan et al., 2018), on the other hand, refers to the disengagement of distractor processing collateral to target enhancement. The major differentiation between the two could be manifested if a proper control condition was used: Instead of comparing directly between target enhancement and distractor suppression, the responses to the two conditions could be compared with a "neutral" condition where neither selection nor suppression is needed (Schneider et al., 2021). In the case of active suppression, a decrease in response to distractor suppression relative to the neutral condition should be observed. In the case of automatic suppression, there would be no difference between the distractor condition and the neutral condition.

Take alpha lateralisation as an example: The contralateral decrease in alpha power may lead to an ipsilateral increase via the interhemispheric inhibitory connection (Schneider et al., 2021). To test whether there is an alpha power increase independent of target selection, Wöstmann et al. (2019) presented the target stimuli in front of the participants and the ignored stimuli on the side. The observation of alpha lateralisation without target-related alpha lateralisation supports the hypothesis that distractor suppression is independent of target selection.

Second, distractibility has been broadly defined as the general proneness to external distraction in the current body of literature. I use the word "broadly" here because the use of the term distractibility ranges from studies of individual traits (e.g., Forster & Lavie, 2016; Kanai et al., 2011), clinical diagnostics (e.g., Mayes & Calhoun, 2002), to the detrimental outcome with distractors in an experiment (e.g., Wais et al., 2012). Furthermore, distractibility has been related to numerous cognitive processes such as working memory capacity (Sörqvist & Rönnberg, 2014) and impulsivity (Amengual et al., 2022). While distractibility represents the proneness to distraction in all studies, the exact cognitive process of interest underlying such "proneness" varied from study to study. While some distractibility studies focused on the endogenous characteristics of individuals on a long temporal scale (e.g., Forster & Lavie, 2014), other studies assumed active suppression of distractors by equating distractibility with the ultimate detrimental influence of distraction (e.g., Gaymard et al., 2003; Wais et al., 2012).

In this thesis, I adopt the definition of distractibility in a strict sense as the endogenous proneness to external distraction. Under this definition, distractibility does not involve the inhibitory process specific to an anticipated distractor, in contrast with active suppression. It describes an endogenous characteristic of individuals that has the potential to fluctuate over time (K.L. Campbell et al., 2012; Forster & Lavie, 2014). Specifically, distractibility may be subserved by the resolution of competition between goal-relevant information and potential external interference, which would involve cognitive control of working memory (Engle, 2002; Lavie, 2010; Sörqvist & Rönnberg, 2014). It may involve the mental capacity to store and prioritise information and has been associated with the frontal cortex (e.g., Chao & Knight, 1995; Gaymard et al., 2003; Wais et al., 2012). However, as mentioned, a lot of previous studies on distractibility used post-stimulus neural measures (e.g., Bidet-Caulet et al., 2015; Chao & Knight, 1995) or the final behavioural detriments (e.g., Wais et al., 2012) as the dependent measure. These post-stimulus neural or behavioural responses may already include the active suppression of distractor. The inference of the neural and behavioural results to distractibility alone should thus be taken with caution.

As an interim summary regarding the many components which contribute to the ultimate distraction, I will go back to the café example with a twist: A puppy runs into the café when an individual is chatting with her friend. Distractibility determines how much she is susceptible to external unexpected distractions. If she is not so distractible, she may keep being engaged in the conversation with her friend without processing the entry of the puppy that much. If she is highly distractible, she may be immediately distracted by the unexpected puppy. Proactive distractor suppression occurs when she knows in advance that the puppy is coming, and she chooses to look away from the entrance. Reactive distractor suppression, on the other hand, occurs when she focuses back on the conversation with her friend after she processes the distracting puppy. Automatic suppression concerns the other distractors in the environment, such as the background music, which are left outside the focus of attention as she is chatting with her friend. The ultimate distraction, which can be indirectly measured as how much she has comprehended from her friend’s speech, is the consequence of the interplay between distractibility and distractor suppression.

1.1.3 Distraction in working memory

Attention and working memory are closely related to each other (Kiyonaga & Egner, 2013; Oberauer, 2019). While attentional filtering is said to be necessary for successful working memory encoding and maintenance (Lorenc et al., 2021; Oberauer, 2019), working memory may be important to attentional selection by holding relevant representations that control where a person directs her attention (A. Baddeley, 1996; de Fockert, 2013). Some researchers proposed that attention and working memory share a conceptual similarity in that both cognitive operations involve the selection of information, which is internal for working memory and external for attention (Cowan, 2005; Kiyonaga & Egner, 2013; Panichello & Buschman, 2021). Given that the selection process, by definition, entails the deselection of task-irrelevant information, it is conceivable that the ability to ignore distractors is also important in working memory as in attentional selection.

Working memory tasks were often used to study distraction (e.g., Colle & Welsh, 1976; West, 1999). One prominent example is the irrelevant sound task (Colle & Welsh, 1976; Salamé & Baddeley, 1982), in which participants are instructed to ignore auditory distractors while holding the order of the target numbers in memory, thereby rehearsing the target numbers in the phonological loop (Baddeley & Hitch, 1974). The irrelevant sound effect was quantified as the worsening of behavioural performance with the presence of auditory distractors. The irrelevant sound effect was robust across different psycho-acoustic features of auditory distractors (Ellermeier & Zimmer, 2014), such as speech distractors (Buchner et al., 2004; Tremblay et al., 2000) or pure tone distractors (D. M. Jones & Macken, 1993; LeCompte et al., 1997). Studies also demonstrated that the temporal information of the distractor (e.g., the temporal occurrence) modulates the working memory performance (Körner et al., 2019; Wöstmann et al., 2020).

This thesis probes into the temporal dynamics of distraction by studying its disruptive influence on working memory. In particular, the first two studies manipulated the temporal onset (Study 1) or the temporal regularity in the onset (Study 2) of distractors presented during the maintenance phase of working memory, and the third study examined the influence of distractors presented simultaneously with the to-be-encoded targets (Study 3). The choice of paradigms, especially for Studies 1 and 2, is for practical reasons: if the target and the distractor are presented at the same time, changing the temporal information of the distractor will inevitably change the temporal relationship between the target and the distractor. It would be empirically difficult to isolate the temporal dynamics of target selection from distraction dynamics. Of note, it does not suggest that the phenomena examined in this thesis do not hold in a perceptual attention task or when target and distractor are presented simultaneously.

1.1.4 Time as an important element of auditory attention

Selective attention is commonly observed in both the visual (e.g., M. I. Posner et al., 1980; Theeuwes, 1993) and the auditory (Cherry, 1953; Shinn-Cunningham, 2008) modalities. Visual inputs and auditory inputs are said to be inherent in different dimensions: while visual inputs are relatively stable, auditory inputs often change over time (Kubovy, 1988; Zoefel & VanRullen, 2017). For example, the coffee mug on the table stays in the same position over time unless someone moves it, but the music in the café keeps unfolding over time. The differences in the inherent properties of the sensory inputs may lead to a difference in the implementation of the attentional filter in the two modalities.

Time is speculated to be an essential element of audition (Kubovy, 1988). From the regular ticking of a clock in the room, to auditory events that have a complex spectrotemporal structure such as speech (Ding et al., 2017), there is often a (quasi-)rhythmic structure in auditory events. Target selection depends on the successful object formation (Shinn-Cunningham, 2008), which is largely based on the spectrotemporal structure in audition (Shamma et al., 2011), in contrast with the spatial configuration important in visual object formation (J. Feldman, 2003). Note that the notion of a bias to space or time in the two modalities does not suggest that vision is strictly spatial and audition strictly temporal. Rather, it suggests that the two systems may be biased in response to temporal or spatial manipulations (Wilsch et al., 2020).

In auditory selective attention, there are mainly two types of interference an auditory distractor can impose on target selection (Mattys et al., 2012; Shinn-Cunningham, 2008). Energetic masking occurs when two auditory inputs are presented concurrently. The overlap of the auditory inputs decreases the intelligibility of the to-be-attended input. An example of energetic masking includes the classic dichotic listening task used to study attentional filtering (e.g., Cherry, 1953; Moray, 1959). Information masking describes the disruptive influence of the distractors that cannot be attributed to energetic masking, which includes factors such as semantic interference (Cooke et al., 2008) and distractor uncertainty (Brungart & Simpson, 2004). This thesis employed energetic masking and/or informational masking in different studies when appropriate. The choice of masking depends on the exact research question in each study.

1.2 The brain dynamics in attentional filtering

The brain activities are inherently rhythmic (Groppe et al., 2013; Keitel & Gross, 2016): the neuronal ensembles periodically fluctuate between higher and lower levels of excitability over time (Bishop, 1932; M. X. Cohen, 2017; Mitzdorf, 1985). Neural oscillations are suggested to be important to the orchestrations between regions of the neural network (Fries, 2015). There has been a growing consensus that the inherent neural oscillations may play a critical role in cognition (Keitel et al., 2022; Schroeder & Lakatos, 2009). Specifically, studies showing modulation of neural oscillatory responses by different cognitive tasks suggest that neural oscillations may serve as the physiological implementation of cognition (Fries, 2015; Herweg et al., 2020; Ward, 2003). Here, I will introduce how the dynamics in the brain are associated with attentional selection to lay the groundwork for motivating how the following features of the dynamical brain may potentially be important to distraction.

1.2.1 The blinking attentional spotlight

The notion that rhythms of the brain are fundamental to the endogenous rhythms of cognition has gained traction in recent years. With the periodic fluctuations of neural excitability over time, there should be times when the brain is more ready to sample the external world (Bishop, 1932; Keitel et al., 2022). The momentary phase of neural oscillations indexes the states of excitability, which may predict the alternation between sampling of the environment with higher or lower precision (VanRullen, 2016). If we densely probe the cognitive system across time with high enough temporal resolution, we will be able to capture a temporal profile of the underlying states of the cognitive system by observing temporal fluctuations of the related behavioural performance.

Attention, which was long considered as a spotlight that shines constantly (M. I. Posner et al., 1980), has recently been hypothesised to be blinking over time (Buschman & Kastner, 2015; VanRullen et al., 2007). The underlying state of attention was probed by varying the onset time of the target stimulus presented after a cue. Attentional sampling was found to wax and wane in a subsecond scale, with evidence from delta/theta frequency (ca. 2 – 8 Hz; Fiebelkorn et al., 2013; Kayser, 2019; Landau & Fries, 2012) to alpha frequency range (ca. 8 – 12 Hz; Busch et al., 2009). Other than the sampling of external attended items, the sampling of internal memory representation also fluctuated in the theta frequency range (Schmid et al., 2022; ter Wal et al., 2021). The behavioural rhythms in attention and memory studies are proposed to originate from the orchestration of the relevant neural networks (Fiebelkorn et al., 2018; Fiebelkorn & Kastner, 2020), such as the frontoparietal network in attentional sampling (Helfrich et al., 2018) or the hippocampus in the sampling of internal memory representation (ter Wal et al., 2021). Nevertheless, researchers have questioned the reliability of the behavioural rhythms of attention with studies showing small (e.g., Plöchl et al., 2022) or even null results (e.g., van der Werf et al., 2022) of temporal dynamics in cognition (Ten Oever et al., 2022).

A prediction central to the notion of rhythmic cognition is that the fluctuations of neural excitability at the relevant brain regions before stimulus onset would predict the fluctuations in behavioural performance (VanRullen, 2016; VanRullen et al., 2011). If behavioural fluctuations originate from the fluctuations in the brain, behavioural performance will vary with the pre/peri-stimulus neural phase at similar frequencies as the behavioural rhythm. Several studies have uncovered such phase-behaviour relationship at frequencies similar to the typical frequencies found in the attentional rhythms (Busch & VanRullen, 2010; Helfrich et al., 2018; Landau et al., 2015). For example, in an electrocorticography study, the theta neural phase in the frontoparietal network was associated with participant's target detection performance, which also showed a temporal structure at 4 to 5 Hz (Helfrich et al., 2018). The behavioural and neural evidence collectively provide affirmative evidence on rhythmic cognition.

With the rich evidence supporting the blinking attentional spotlight, however, the evidence of whether the vulnerability to distraction, i.e., distractibility, may also exhibit temporal fluctuations is scarce. Studies have shown that the distractor onset time may modulate its disruptive influence on task performance (Körner et al., 2019; Wöstmann et al., 2020). Regarding the temporal dynamics of distraction, preliminary evidence suggests that the behavioural and neural measures of distraction may fluctuate at a slow temporal scale (< 4 Hz; Wöstmann et al., 2020). Consistent with the notion that distraction may also be rhythmic, a previous study showed a stronger phasic relationship between pre-target theta rhythm and stimulus detection when the stimulus was in the unattended location than in the attended location (A. M. Harris et al., 2018), suggesting that fluctuations in neural excitability may also explain the processing of stimuli outside of the attentional spotlight. These studies serve as a precursor pointing to the notion that distractibility exhibits temporal dynamics.

1.2.2 Do exogenous rhythms modulate attention?

Rhythms are ubiquitous in the external environment, and the human brain often makes use of these exogenous rhythms to guide behaviour (Lakatos et al., 2019). For instance, human's sleep-wake cycle (i.e., circadian rhythm) is aligned with the rising and setting of the sun (i.e., the diurnal cycle). It is natural to tap along with the tempo of the music to which one is listening. While the previous section introduced the endogenous fluctuations of attention, this section highlights the current literature on how exogenous rhythms may play a role in target selection.

The dynamic attending theory posits that attentional resources are temporally aligned, that is, entrained, to the exogenous, to-be-attended rhythmic stream (Large & Jones, 1999). The theory adopts the view that attention has a rhythmic property, with waxing and waning attentional resources over time. In the face of exogenous rhythmic events, the attentional rhythm may adapt to the temporal regularity embedded in the events. Temporally regular events are predictable in time, which allows the attentional system to form the prediction of when the next event may occur (i.e., temporal expectation). The formation of temporal expectation facilitates the cognitive system to optimally allocate resources to the predicted onset time of the event, thereby facilitating the processing of the sensory event.

The dynamic attending theory has gained support from a rich body of literature on the behavioural level (e.g., Barnes & Jones, 2000; Correa & Nobre, 2008; M. R. Jones, 1981; Mathewson et al., 2012). Behavioural performance such as accuracy/sensitivity (e.g., Barnes & Jones, 2000; Cravo et al., 2013; M. R. Jones et al., 2002; Rohenkohl et al., 2012) and reaction time (e.g., Lakatos et al., 2008; Morillon et al., 2016) is better with temporally regular stimuli versus temporally irregular stimuli. One hypothesis based on the dynamic attending theory is that after being entrained to the exogenous rhythm, the cognitive system maintained the attentional rhythm for a few cycles (Lakatos et al., 2013). Deviating from the expected stimulus onset will thus have a detrimental influence on target selection (Hickok et al., 2015; M. R. Jones et al., 2002; but see Bauer et al., 2015).

Entrainment, on the neural level, is said to be implemented via the temporal alignment of an optimal neural phase to the predicted onset time of the exogenous input (Lakatos et al., 2019; Obleser & Kayser, 2019). One of the neural outcomes of entrainment is the concentration of neural phase at frequencies similar to the frequency of the exogenous rhythm (e.g., Henry & Obleser, 2012; Stefanics et al., 2010). For instance, in Lakatos et al. (2008), temporally regular visual and auditory streams were presented in an interleaving manner (i.e., anti-phasic). Macaque monkeys were trained to attend to either of the two streams and respond to the deviant target. Delta oscillations in the primary visual cortex were entrained to the rhythm of the attended visual stream, as shown by delta phase coherence. Interestingly, the delta phase was concentrated at the anti-phase when the visual stream was ignored.

The opposite phasic concentration between the attended and the ignored stream begs a question: Does entrainment require attention? If entrainment is specific to the processing of attended stimuli, the anti-phasic concentration in the ignored stream may be a by-product of the phase concentration observed in the attended stream. Alternatively, entrainment may also take place when the external events are ignored, leading to an independent phase concentration that is anti-phasic of the optimal phase for attention. To test against the two hypotheses, one can examine if one's behavioural performance or neural response is modulated by the temporal regularity of distractors in the absence of an attended rhythm.

Surprisingly, the evidence on the behavioural disruption of temporally (ir)regular distractors is scant and inconsistent. For example, Makov & Zion Golumbic, (2020) showed that participants were better at detecting the deviance in unmasked targets when the concurrently presented distractors were temporally regular versus irregular. In the context of the irrelevant sound task, the serial recall performance was facilitated by (D. M. Jones & Macken, 1995) or disrupted (Parmentier & Beaman, 2015) with temporally regular distractors in different studies. Given the inconsistency in the current literature, a systematic investigation that probes into the scope of behavioural detriment with regard to the temporal regularity of distractors is warranted.

1.2.3 Brain dynamics in feature-based prediction

The human brain is posited as an active agent who constantly makes predictions of future event based on past experience (Friston, 2005; Ivry & Knight, 2002; Von Helmholtz, 1867). In essence, the brain forms a generative model of the world based on the regularities embedded in the sensory evidence. For example, one should predict that the sun will rise from the east because it has been rising every day from the east. If the upcoming event does not match with the prediction (e.g., the sun comes up from the west today), a prediction error will occur to inform the model to update for the next prediction. The predictive process is not limited to predicting when (i.e., temporal prediction; see the previous section), but also predicting what (i.e., feature-based prediction; Schwartze et al., 2011) the upcoming stimulus would be.

Attention and prediction are two major pillars in the study of human cognition. Studies using a passive listening task showed that even outside the focus of attention, the brain is capable of forming a generative model based on the regularities in the task-irrelevant events (Garrido et al., 2009; Näätänen et al., 2007; Winkler & Czigler, 2012). The extracted regularities ranged from the global probability of a stimulus feature (López-Caballero et al., 2016; Sato et al., 2000) to the local transition probability between stimuli (Koelsch et al., 2016; Lieder et al., 2013; Mittag et al., 2016). The deviation from the prediction based on the generative model would elicit mismatch negativity (MMN; Näätänen & Michie, 1979), which is theorised as a prediction error signal that calls for a model update (Winkler, 2007). The converging evidence on prediction outside of attention raised two questions: How would the neural response be modulated when the predictive process occurs within the spotlight of attention? Would task-irrelevant events outside of the attentional spotlight with different levels of predictability possess different potency to distract? This thesis is mainly concerned with the latter question in relation to distraction. I will nevertheless briefly discuss the current literature pertaining to the two questions for comprehensiveness.

There has been a divergence in the views regarding the relationship between attention and prediction (Heilbron & Chait, 2018; Schröger et al., 2015). The first view theorised attention as a gain that amplifies the neural response irrespective of prediction (e.g., Garrido et al., 2018). The second view treated attention as precision inference on the reliability of the prediction error (Feldman & Friston, 2010). In such a case, predictable stimuli would have a higher precision, leading to a larger amplification of the neural response compared with unpredictable stimuli by attention (Hsu et al., 2014; Kok et al., 2012). The dynamics between attention and prediction have still been under debate as both views received empirical support (e.g., Garrido et al., 2018; Hsu et al., 2014; Kok et al., 2012). For example, the stimulus-evoked responses were larger only when the stimuli were both attended and predictable in Hsu et al. (2014), concurring the latter view where attention and prediction interact. However, Garrido et al. (2018) showed that attention enhanced neural responses in the predictable and unpredictable conditions to the same extent, supporting the former view.

If the brain can extract regularities and make predictions from the task-irrelevant events, do different levels of predictability in the task-irrelevant events lead to a different potency of these events to distract? The prevalent view holds that predictable distractors yield less distraction due to expectation suppression (Noonan et al., 2018; van Moorselaar & Slagter, 2020). Expectation suppression posits that the processing of expected distractors is attenuated as they contain little information (Noonan et al., 2018). Predictable distractors, which lead to a higher expectation, should thus be less distracting and reduce the corresponding behavioural detriments. Studies on spatial prediction largely agree with the notion by showing better behavioural performance with a predictable distractor location (Failing, Wang, et al., 2019; Noonan et al., 2016; B. Wang et al., 2019).

Outside the realm of spatial prediction, however, empirical results depict a rather complex picture of how distractor predictability may play a role in the ultimate degree of distraction. Southwell et al. (2017) demonstrated that change detection performance was better with repeating tone distractors versus random tone distractors. Another study found that the influence of context predictability hinged on the dissimilarity between the target and distractor (Töllner et al., 2015). On the other hand, trial-wise predictability of the distractor's presence (Bogaerts et al., 2022) and semantic predictability of the distractors (Wöstmann & Obleser, 2016) did not modulate behavioural performance. The inconsistent results from these studies suggest that there may be some underlying factors that potentially modulate the influence of feature-based prediction on distractor processing.

1.3 Research questions

The overarching aim of this thesis is to elucidate the temporal dynamics of distraction. Traditionally, attentional selection has been the focus when studying attentional filtering in cognitive neuroscience, with the theoretical foundation of selective attention leaning towards the selection of task-relevant targets (M. I. Posner et al., 1980). Nevertheless, task-irrelevant distractors are everywhere in the external environment. Empirical evidence shows that our brain does not fully shunt the distractors out of the attention system. Rather, the brain is prone to external distractors (e.g., Chao & Knight, 1995; Gaspar & McDonald, 2014) and may engage in active suppression of the distractors (Geng, 2014; Schneider et al., 2018). As we are constantly bombarded by external distractors, the question arises: How do the temporal mechanisms of distraction unfold in time?

To this end, three behavioural and electrophysiological studies with a total of 136 participants probed each aspect of the potential temporal mechanisms of distraction. Figure 1.2A illustrates the major elements of this thesis, namely, endogenous brain dynamics and exogenous distractor dynamics, using the barking puppies as an example of distractors. Study 1 (Chapter 3) sheds light on the endogenous rhythms of distractibility by relating the momentary neural state with the ultimate behavioural detriments of distraction (Figure 1.2B, top). Distractibility is a construct that has long been assumed to, if at all, only change on a slow temporal scale, such as over developmental stages (K.L. Campbell et al., 2012) or within an experimental session (Forster & Lavie, 2014). This study aims at revealing the dynamic nature of distractibility on a faster, subsecond, temporal scale.

Having uncovered an endogenous distractibility rhythm, Study 2 (Chapter 4) asks if the proneness to distraction can be entrained, by studying whether temporally regular distractors influence the eventual memory recall of targets (Figure 1.2B, middle). The current evidence on the effect of distractors' regularity in time is inconsistent, with results supporting the facilitation (D. M. Jones & Macken, 1995) and the disruption (Parmentier & Beaman, 2015) by temporally regular distractors. In a series of 4 behavioural experiments, this study systematically investigates the potential factors influencing the modulatory effect of the temporal regularity of distractors on both the precision of memory representation (i.e., accuracy) and response behaviour (e.g., speed and confidence).

As no strong evidence was found on the role of temporal prediction of the distractor in modulating the precision of memory representation, Study 3 moves to elucidating the brain dynamics associated with feature-based prediction, i.e., predicting what the stimulus is, in distraction (Chapter 5; Figure 1.2B, bottom). The load theory of attention (Lavie, 1995) is a well-received framework depicting how perceptual load and cognitive load modulate distractor interference. However, whether the load theory still holds in the auditory modality remains unclear (S. Murphy et al., 2017). This study asks whether the impact of feature-based distractor prediction on behavioural and neural responses hinges on perceptual or cognitive load, based on the framework of the load theory of attention. In summary, this thesis aims at uncovering the many facets of how auditory distraction unfolds in time.

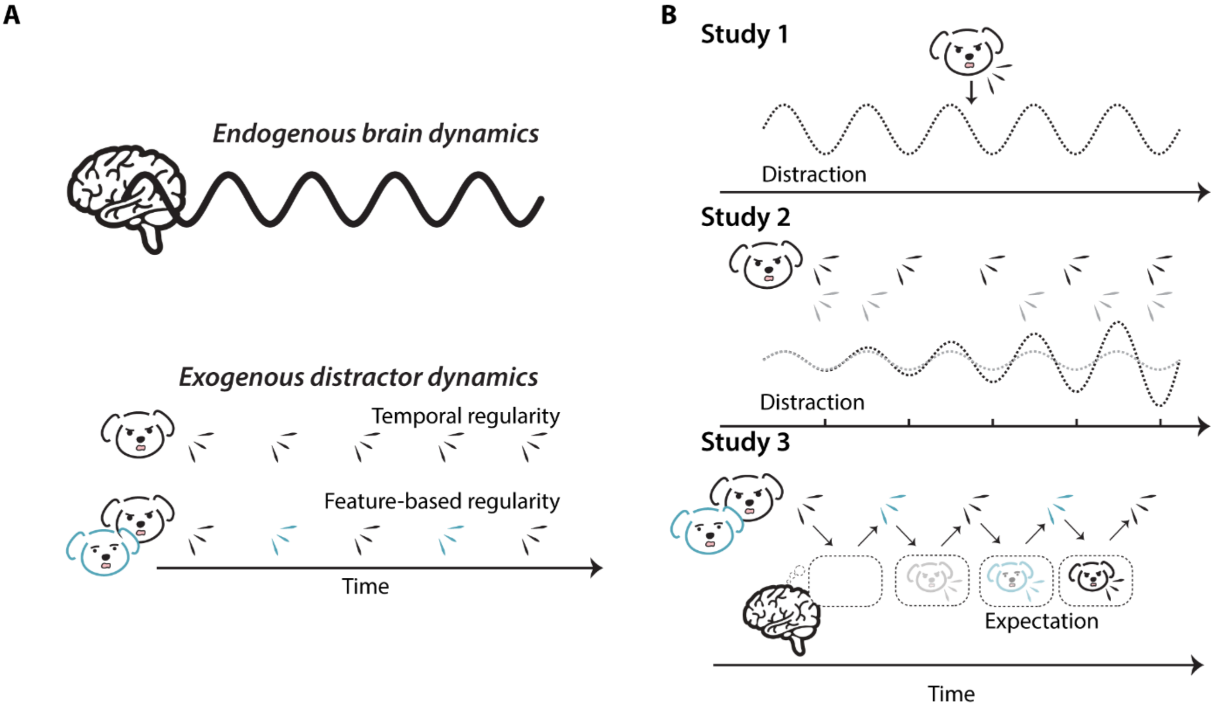

Figure 1.2. Overview of the 3 studies in the present thesis on the temporal dynamics of distraction. The left column (A) displays the major themes in this thesis, namely the endogenous dynamics of the brain (top) and exogenous dynamics in distractors, which include temporal and feature-based regularity (bottom). The right column (B) depicts the central research question for each study in this thesis. Study 1 (top) focuses on capturing the cyclical fluctuations of distractibility, which would result in fluctuations in the behavioural measure of distraction (dashed line). Study 2 (middle) studies whether the distractibility dynamics can be entrained by temporally regular distractors (black dog barks) compared to temporally irregular distractors (grey dog barks). Study 3 (bottom) investigates if the brain forms distractor expectations from the feature-based regularity (identity of the barking dog).

2. Methodological background

In this chapter, I will first briefly overview the choice of stimulus materials across studies in this thesis. Second, I will introduce the underlying neurophysiological mechanism of electroencephalography (EEG), the basics of EEG analyses, and the source localization method used in the thesis. Specific methodological details for each study will be introduced in the methods section of the corresponding chapter.

2.1 Stimulus materials: Essential features of distractors

Two types of distractors were used in this thesis: pitch and speech stimuli. For each experiment, pitch or speech stimuli were chosen based on two major considerations: 1) the stimulus's potency to distract, and 2) the temporal precision of the stimulus.

The distractor's potency to distract can be quantified indirectly by measuring the detriment in the behavioural performance relating to the target stimuli (Wöstmann et al., 2022): A more distracting distractor will interfere with the target performance to a larger extent, rendering poorer behavioural performance. One can argue that an absence of behavioural effect with distractors signifies a successful suppression of the distractor. However, the absence of a distractor effect may be attributed to the lack of distractor interference. In this thesis, the distractor's potency to distract was ensured by either comparing the behavioural performance between distractor present or absent conditions (Studies 1 and 2), or between distractors with different strengths (e.g., signal-to-noise ratio with targets, Study 3).

As this thesis mainly focuses on the temporal dynamics of distraction, the temporal precision of the distractor is also important. Changes in stimulus properties such as duration (Kaukoranta et al., 1989) or inter-stimulus interval (Pereira et al., 2014) have been shown to modulate the corresponding neural response. Temporally imprecise stimuli may thus be a potential confound. In Study 1 and Study 2 where the effect of temporal onset on distraction were probed, the temporal precision in distractors was prioritised.

When should pitch or speech stimuli be used? While speech materials have been shown to exert a large detrimental influence on working memory (Ellermeier & Zimmer, 2014), pitch materials can be manipulated with higher temporal precision. Study 1 focuses on uncovering the endogenous rhythm of distraction, which requires high temporal precision in the distractors. Therefore, pure tones were used for both target tones and distractor tone structures to ensure temporal precision. In Study 2, pure tone distractors were used in Experiment 1 and 2 to probe into the modulatory effect of the temporal regularity of distractors. With an absence of a temporal regularity effect in those experiments, speech distractors were used in Experiment 3 and 4 to increase the degree of distraction. When using speech stimuli as distractors, we increased the temporal precision of the distractors by shortening all spoken numbers used to a fixed duration (i.e., 350 ms) by using the Praat software. In Study 3, speech distractors were used as the potency of distractor to distract was prioritised over temporal precision, as feature-based predictability, instead of temporal predictability, is the main interest of this study.

2.2 Irrelevant sound paradigm

In Studies 1 and 2, variants of the irrelevant sound paradigm (Colle & Welsh, 1976; Salamé & Baddeley, 1982) were used to study the temporal mechanisms of distraction. Here, I will briefly describe the basic structure of the experimental design used in these studies.

Essentially, the irrelevant sound paradigm consists of three phases: encoding, maintenance, and retrieval. During the encoding phase, the to-be-remembered stimuli are presented. While the to-be-remembered stimuli were a sequence of spoken numbers typically used (e.g., Salamé & Baddeley, 1989), other to-be-remembered stimuli such as tone-frequency (Study 1) or an array of visual numbers (Experiment 4 in Study 2) were used in this thesis. During the maintenance phase, participants are instructed to maintain the memory representation of the encoded item while ignoring the auditory distractors presented. During the retrieval phase, participants had to report how well they remember the to-be-remembered stimuli by either comparing the to-be-remembered stimuli with a probe stimulus (in Study 1 and Experiment 4 in Study 2) or recall the order of the to-be-remembered stimuli (in Experiment 1 to 3 in Study 2). The distractor's interference is measured by the behavioural detriment in the task with or without distractors, or with different levels of distraction.

2.3 Electroencephalography

The current thesis employed electroencephalography (EEG) to study the dynamics of the brain's neural activity. EEG is a measure of the electrical activities in the brain (Berger, 1931). It has a relatively high temporal resolution compared to other brain imaging methods which indirectly measured blood flow associating with neuronal activation (e.g., MRI, fNIRS;

Sejnowski et al., 2014). The high temporal resolution of EEG makes it a good candidate for the investigation of temporal dynamics of the brain.

2.3.1 The neurophysiological basis of EEG

Essentially, EEG measures the voltage fluctuations of the extracellular currents integrated across a neuronal population. The amplitude of the electrical activities should be large enough to be detected by the electrodes placed on the scalp. Hence, the post-synaptic activities of the pyramidal neurons are considered the major contributor to the scalp-level EEG activities. The parallel organization of the pyramidal cells (Mitzdorf, 1985) and the relatively slow temporal integration of the post-synaptic potential (Jackson & Bolger, 2014) allows the summation of the electrical activities across a neuronal ensemble. Excitatory postsynaptic activity involves an influx of the positive charged Ca+ and Na+ ions into the neuron, creating a negatively charged extracellular region, i.e., sink, relative to the other regions of the neuron. The voltage difference between the two ends of a neuron creates a dipole, the summation of which across a neuronal ensemble is detected by scalp EEG (Nunez & Srinivasan, 2006).

Each dipole contributes to the voltage measured at all electrodes through volume conduction. However, the relative contribution of the dipole depends on its orientation and its distance from the scalp electrode. For instance, radial dipoles that are closer to the surface have a stronger impact on the surface EEG placed above the dipole. Depending on the orientation of the dipoles, the resultant scalp distribution may be vastly different even if the dipoles are in proximation with one another (Jackson & Bolger, 2014). It is thus essential, in order to localize the neural response of interest, to apply source localization methods (see Section 2.3.3).

2.3.2 The basics of EEG analyses

The excitation and inhibition of a neuronal ensemble wax and wane over time, producing a rhythmic, oscillatory, pattern on EEG (Bishop, 1932). We can study EEG signals by quantifying their temporal and spectral dynamics using, e.g., amplitude, power, and phase. The physiological underpinning of each property has been discussed in previous literature (Buzsáki & Draguhn, 2004; Sauseng & Klimesch, 2008; Woertz et al., 2004). In the following, I will explain the basics of these oscillatory properties and the possible neurophysiological underpinnings.

Figure 2.1 shows the oscillatory properties using a 5-Hz sine wave as an example. The frequency of a signal corresponds to the number of cycles the signal has per second. For instance, a theta oscillation roughly has 3 to 7 cycles per second (i.e., 3 – 7 Hz). Amplitude refers to the strength of the signal, which is usually measured as power (the square of amplitude). Phase refers to the angular/polar representation of the signal at a given time point (i.e., peak refers to the highest point of a signal, and trough the lowest). Physiologically, EEG amplitude is said to reflect the strength of the sustained activity of a neuronal ensemble, which has a temporal resolution of hundreds of milliseconds (Woertz et al., 2004). Instantaneous phase of EEG, on the other hand, is associated with the momentary firing patterns of a neuronal ensemble (Buzsáki & Draguhn, 2004; K. D. Harris et al., 2002; Hirase et al., 1999).

In this thesis, different analysis methods are used depending on the respective research question. For instance, event-related potential (ERP) technique was used to study the amplitude of stimulus-evoked neural responses that are consistent in timing (i.e., phase-locked) in Study 1 and Study 3. In Study 1, trial-wise instantaneous phase values were captured to investigate the momentary fluctuations of the neural oscillatory response. In Study 3, oscillatory power in the alpha frequency band (i.e., 8 – 12 Hz) was measured to examine the strength of neural activity. The analyses used in each study will be described, in detail, in the method sections of the respective chapter.

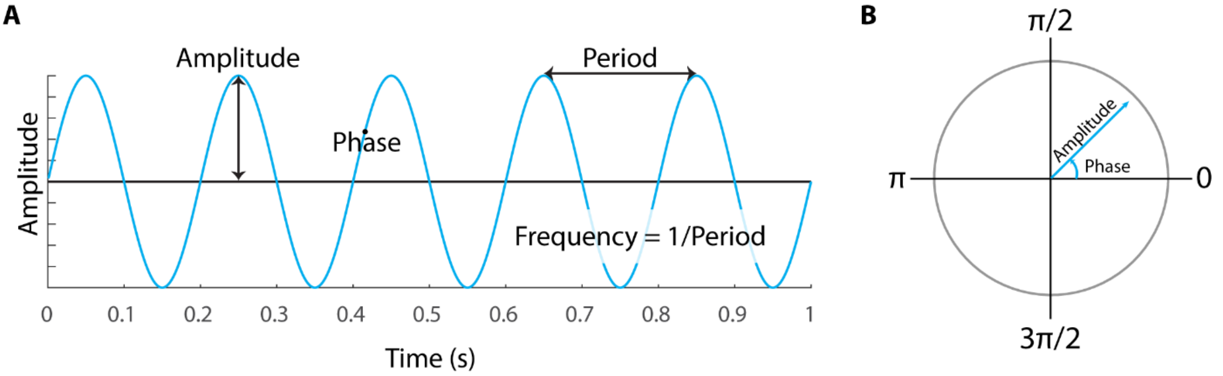

Figure 2.1. Illustration of a 5 Hz rhythm in the time domain (A) or as a unit cycle (B).

2.3.3 Source localisation

The inverse problem states that there is no unique solution in deriving the underlying source activities from the surface sensor (i.e., electrode) data. Different methods have been derived throughout the years to mitigate the problem (e.g., equivalent dipole, LORETA, beamformer etc; Halder et al., 2019). The beamformer approach has gained popularity in the past decades as it does not require a priori assumptions about the number nor the distribution of sources. In Study 1, one of the beamformer localisation methods called linearly constrained minimum variance (LCMV; Sekihara & Nagarajan, 2008; Van Veen et al., 1997) was used to localise the dynamics in distractibility. The beamformer localisation method will be briefly described here.

The basic ingredients required for the beamformer source localisation are as follows: A forward model describes how each source location contributes to the spatial distribution on the sensor space. To obtain the forward model, the following elements are needed: First, a source model derived from an individual MRI scan is needed to indicate the locations of the sources. In case when individual MRI scan is not available, a standard MRI template can be used. Second, a head model (e.g., the standard boundary element method volume conduction model; Fuchs et al., 2002) is needed to describe how the source currents flow through the volume conductor, which entails the brain, the skull, and the scalp tissue. Third, electrode positions are needed for the co-registration between the MRI scan and the electrodes. All three elements are used to estimate the lead field matrix, which contains the solution relating the source electrical activity and the potential on the EEG electrodes (Van Veen et al., 1997).

The inverse model is estimated with a goal to transform the data in the sensor space to the source space by applying a set of weights (i.e., spatial filter) on the sensor data (Westner et al., 2022). The spatial filter estimates the relative contribution of each channel to the respective source location. The exact algorithm of estimating the spatial filter differs between different source localization methods. The LCMV method uses the lead field matrix and the covariance matrix of the time-series EEG data across channels to estimate the spatial filter (Van Veen et al., 1997). The covariance matrix is derived from the EEG data at the time window of interest. At each source location, the relative contributions of the sensor signals are estimated with the goal to maximise the output of the given source location and minimise the output from all other source locations.

With the estimated spatial filter, the time-series data on the sensor space can be projected onto the source space by multiplying the data matrix with the spatial filter. The neural signature of interest, such as pre-stimulus single-trial neural phase (Study 1), can then be calculated on the source space

3. Study 1: Slow neural oscillations explain temporal fluctuations in distractibility[1]

3.1 Introduction

Selective attention enables humans to focus on relevant information at the expense of distraction. The brain prioritizes representations of relevant events while filtering out task-irrelevant distractors (Desimone & Duncan, 1995; Picton et al., 1971). Recent research posited that distractor processing is not merely collateral to attentional sampling of targets but may follow its own dynamics (Schneider et al., 2018; Wöstmann et al., 2019, 2020). The behavioural detriments induced by different kinds of distractors (i.e., *distraction*) and the neuro-cognitive mechanisms that counteract distraction (i.e., *suppression*) have been studied in some detail (Bonnefond & Jensen, 2012; Geng & DiQuattro, 2010; van Moorselaar et al., 2020; Weisz et al., 2020; Wöstmann et al., 2019). However, the temporal dynamics and the neurobiological basis of the proneness to distraction (i.e., *distractibility*) are largely unknown.

Distractibility has long been neglected in the theoretical formulation of rhythmic attention. Originally assumed to be static (M. I. Posner et al., 1980), the attentional spotlight was proposed to be blinking at a subsecond time scale in a theta-like rhythm (i.e., 3–8 Hz; Buschman & Kastner, 2015; Fiebelkorn & Kastner, 2019). Behaviourally, it is manifested via the waxing and waning of behavioural performance in target selection (Fiebelkorn et al., 2013; Ho et al., 2017; Kubetschek & Kayser, 2021; Landau & Fries, 2012) or working memory (Schmid et al., 2022; ter Wal et al., 2021) performance at similar frequencies. However, the temporal dynamics outside of the attentional spotlight are not well understood. While previous research studied how distractibility unfolds on relatively long temporal scales of minutes (i.e., during an experimental session; Forster & Lavie, 2014) or years (i.e., across stages of development; K.L. Campbell et al., 2012; Kannass et al., 2006), we found preliminary evidence for fluctuating distractibility on a subsecond scale following rhythmic presentation of auditory targets (Wöstmann et al., 2020). To isolate distractibility dynamics from rhythmic entrainment or preparatory suppression, we here employ a design that uses non-rhythmic stimuli and distractors that occur unexpectedly.

A central prediction of rhythmic attention is that the phase of slow neural oscillations explains fluctuations in behaviour (VanRullen, 2016). The prediction is based on the notion that rhythmic attention arises from the periodic excitability of the attention-related brain network

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[1] This chapter is adapted from the preprint published by Lui et al. (2022)

(Fiebelkorn & Kastner, 2019; VanRullen, 2016). In the human brain, theta neural phase (3–8 Hz) is assumed to reflect moment-to-moment changes in neural excitability (Lakatos et al., 2005). Theta phase in brain regions beyond sensory cortices, such as fronto-parietal regions and the hippocampus, has been associated with fluctuations in target detection (Helfrich et al., 2018) and working memory encoding (Rutishauser et al., 2010; Siegel et al., 2009), respectively. While previous research has related distractibility to supra-modal regions in frontal (Chao & Knight, 1995; Wais et al., 2012) or parietal (Kanai et al., 2011) cortex, it is unclear whether and in which networks the momentary neural dynamics may subserve the waxing and waning of distractibility.

Here, we ask if the brain spontaneously alternates between states of higher and lower distractibility and whether such fluctuations have the potency to explain behavioural consequences of distraction. If so, we would expect to observe a brain-behaviour relation between the pre-distractor brain state and the distractor-induced detriment in task performance. To this end, we employed a pitch discrimination task wherein an auditory distractor could occur at variable and unexpected times in-between two target tones. A total of 17,280 behavioural and neural responses in the electroencephalogram (EEG) in N=30 participants revealed that behavioural sensitivity and distractor-evoked neural responses fluctuated in sync across distractor onset times in ~3–5 cycles per second. Critically, pre-distractor theta phase in left inferior frontal and insular cortex regions explained behavioural performance fluctuations. These effects were absent in trials without distractors, reinforcing their specificity to distractor-related neural processing.

3.2 Methods

3.2.1 Participants

Thirty participants (20 females, 10 males; mean age = 23.67, SD = 3.56) took part in the EEG experiment. They provided written informed consent and were compensated by either €10/hour or course credit. Participants were right-handed according to the Edinburgh Handedness Inventory (Oldfield, 1971) (mean score = 92), with self-reported normal hearing, normal or corrected-to-normal vision, and no psychological or neurological disorders. All procedures of the current study were approved by the ethics committee of the University of Lübeck.

3.2.2 Stimuli and procedure

Participants performed a pitch discrimination task wherein they decided whether the first (tone 1) and the second (tone 2) target tones in a trial were the same or different in pitch. Prior to the experiment, they were instructed to answer as accurately and as fast as possible. The target tones were 75 ms long pure tones with 5 ms rise and fall periods. In each trial, the frequencies of tone 1 were randomly selected between musical note A#3 (233 Hz) and G#5 (830.6 Hz), while that of tone 2 was either the same (50%) or different (higher or lower, 25% each) in frequency compared to tone 1.

The pitch difference between tone 1 and tone 2 was titrated for each participant with an adaptive task (see below). The offset-to-onset interval between tone 1 and tone 2 was 1550 ms. Each distractor stimulus comprised 10 consecutive pure tones with 40 ms duration (400 ms in total). The frequencies of the pure tones in each distractor stimulus were randomly selected among the 12 tones between A#3 and G#5 with whole tone steps (A#3, C4, D4, E4, F#4, G#4, A#4, C5, D5, E5, F#5, and G#5), with the constraint that there would be no repetition between consecutive tones. Each of the 12 tone frequencies appeared at each of the 10 positions with equal probability across trials.

In-between the two target tones, a distractor was presented in 50% of trials (distractor-present condition) and no distractor was presented in the remaining trials (distractor-absent condition). In the distractor-present condition, the distractor was presented at one of 24 distractor onset times (0 ms to 1150 ms, 50-ms steps, relative to the offset of tone 1), which was selected at random on each trial. After the offset of target tone 2, participants had a 2000 ms response time window. To avoid potential temporal predictability effects of the onset of the next trial, the inter-trial intervals were randomly selected from a truncated exponential distribution (mean = 1460 ms), ranging between 730 and 3270 ms.

The trial order was pseudo-randomized with no repetition in probe tone frequency and distractor onset for any two consecutive trials. In total, there were 12 trials for each unique condition (distractor-present/absent x distractor onset x same/different target pitch) and 1152 trials for the whole experiment. All auditory materials were presented via Sennheiser headphones (HD 25-1 II). Responses were made using a response box (The Black Box Toolkit). The assignment of buttons to the response options (“same” or “different”) was counterbalanced across participants. Stimuli were presented via Matlab (MathWorks, Inc., Natick, USA) and Psychtoolbox (Brainard, 1997). The auditory stimuli were presented at approximately 70 dB SPL.

3.2.3 Adaptive staircase procedure

Prior to the main experiment, each participant's threshold for the pitch discrimination task was titrated using an adaptive staircase procedure, implemented in the Palamedes toolbox (Prins & Kingdom, 2018) for Matlab. For the initial 11 participants, the threshold was titrated to an approximate accuracy of 70.7%. As the overall accuracy was relatively high even after the adaptive staircase procedure for these 11 participants (mean = 79.59%, SD = 10.43%), the final 16 participants performed an adaptive procedure altered to yield approximately 65% accuracy instead. Due to technical issues, the performance of the remaining three participants was tracked at 35% accuracy. As all relevant statistical analyses in the present study are within-subject, and as paired t-tests (2-tailed) comparing the behavioural performance between distractor-absent and distractor-present conditions were significant with ($t_{29} = 8.11$, $p < .001$) and without ($t_{26} = 9.41$, $p < .001$) these participants, their data were included in the final analysis.

Each participant went through the adaptive staircase procedure two to three times, depending on the stability of the tracked threshold. There were in total 30 trials for each run of the adaptive staircase procedure with an initial pitch difference of 100 cents (i.e. 1 semitone) between tone 1 and 2. The minimum and maximum pitch difference possible in the task was 2 cents and 2000 cents, respectively. For the procedure which tracked performance at ~70.7%, a two-down one-up procedure was used. Specifically, the pitch differences would decrease in steps of 10 cents if participants responded correctly (i.e., different), or increase in steps of 10 cents if participants responded incorrectly (i.e., same) for 2 consecutive trials. For the procedure which tracked performance at ~65% procedure, the pitch differences would decrease in steps of 7 cents if participants answered correctly or increase in steps of 13 cents if they answered incorrectly. The pitch difference used in the main experiment was calculated by averaging the final 10 trials in the tracking run which converged to the most stable threshold, determined by visual inspection, in the ~70.7% procedure. The same procedure was used to average the final 6 trials in the ~65% procedure. The overall accuracy averaged across all participants in the actual experiment was 73.58% (SD = 12.12%).

3.2.4 Behavioural data analysis

To understand how distractors affect pitch discrimination performance in the framework of signal detection theory, we calculated sensitivity (d') and criterion (c) separately for distractor-present and -absent conditions, using the Palamedes toolbox (Prins & Kingdom, 2018) and the following formulas:

(Formula 3.1) Sensitivity = z (Hit rate) – z (False alarm rate)

(Formula 3.2) Criterion = –0.5 * (z (Hit rate) + z (False alarm rate))

Hit rate was defined as the "different" response when the two tones were different in pitch, and false alarm rate was the "different" response when the two tones were the same in pitch. Extreme values (0 or 1) of Hit rate or False alarm rate were adjusted (Macmillan & Kaplan, 1985): A rate of 0 was adjusted by dividing 1 by the number of trials multiplied by 2; while a value of 1 was adjusted by subtracting the same value from 1. Paired samples t-tests (2-tailed) were used to compare sensitivity and criterion in distractor-present versus -absent conditions.

To study the modulation of distractor onset times on behavioural measures in the distractor-present condition, sensitivity for each distractor onset time was calculated, resulting in a behavioural time course as a function of distractor onset time for each individual participant (see Figure S3.1 & S3.2).

3.2.5 EEG recording and pre-processing

The experiment was conducted in an electrically shielded sound-attenuated room. A modified 10-20 international system with 64 Ag/Ag-Cl electrodes was used to record the EEG with a sampling rate of 1000 Hz (actiCHamp, Brain Products, München, Germany). The EEG recordings were band-pass filtered online from direct current (DC) to 280 Hz. TP9 was used as the online reference and FPz as the ground electrode. Impedances were kept below 20 kOhm for all but one participant.

Matlab R2018a (MathWorks, Inc., Natick, USA) and the Fieldtrip toolbox (Oostenveld et al., 2011) were used to pre-process and analyse EEG data. The continuous EEG data were filtered (high-pass, 1 Hz; low-pass, 100 Hz) before they were segmented into epochs (-2 to 2.5s) time-locked to tone 1 onset. Independent component analysis (ICA) was used to identify and reject components corresponding to artefacts such as eye blinks, eye movements, and muscle activity (average percentage of components removed = 26.46%, SD = 8.89%). Afterwards, EEG data were re-referenced to the average of all electrodes. Epochs with amplitude changes >160 microvolts were rejected (average percentage of epochs removed = 1.35%, SD = 2%).

To obtain distractor-evoked neural responses, data were re-epoched to the onset of the distractor (-1 to 1 s) with a 200ms baseline period. Epochs belonging to the same conditions (distractor-present/absent) and distractor onset time (0 – 1150ms, 50-ms steps) were then averaged into ERP waveforms. The spectral amplitude of distractor-evoked responses at 25 Hz, which corresponds to the temporal structure of the distractor, was extracted using FFT on the ERP waveform in the time window from 0 to 520ms after distractor onset. Spectral amplitude was averaged across electrodes F1, Fz, F2, FC1, FCz, and FC2. For each participant, the 24 spectral amplitudes, corresponding to the 24 distractor onset times, resulted in a neural time course of distractor processing as a function of distractor onset time (see Figure S3.1 & S3.2).

Distractor-evoked inter-trial phase coherence (ITPC) was also calculated across frequencies (1 – 10 Hz, 1-Hz steps) and time windows (-0.2 – 0.7 s, 0.05-s steps) for each electrode. First, Fourier coefficients were calculated (using windows with a fixed length of 0.5 s; hanning taper). Then, the complex Fourier coefficients were divided by their magnitude and averaged across trials. ITPC was calculated by taking the absolute value (i.e., magnitude) of the average complex coefficient.

3.2.6 Modulation of neural and behavioural measures by distractor onset time

To test whether and how distractor onset time modulates neural and behavioural measures, we used linear mixed-effect models with sine- and cosine-transformed distractor onset time, similar to Wöstmann et al. (2020). For time courses of sensitivity and spectral amplitude of the distractor-evoked ERP at 25 Hz separately, we first subtracted the individually fitted quadratic trend (computed with the polyfit function in Matlab) from the original time course for each participant (see Figure S3.1 & S3.2) as the quadratic trend was not of interest in the current study (Huang et al., 2015).

Then, we designed sine- and cosine-transformed distractor onset time vectors using the following formulas,

(Formula 3.3) $\text{Sine predictor} = \sin(2 * \pi * f * \text{distractor onset time})$

(Formula 3.4) $$\text{Cosine predictor} = \cos(2 * \pi * f * \text{distractor onset time})$$

Where f denotes the frequency of interest (0.5 – 8 Hz, 0.5-Hz steps). Next, we regressed the detrended sensitivity and spectral amplitude of ERP time courses on sine and cosine predictors using linear mixed models (using the fitlme function in Matlab) for each frequency of interest using the following formulas:

(Formula 3.5) $$z(\text{sensitivity}) \sim z(\text{sine predictor}) + z(\text{cosine predictor}) + (1|\text{participant})$$

(Formula 3.6) $$z(\text{25-Hz ERP}) \sim z(\text{sine predictor}) + z(\text{cosine predictor}) + (1|\text{participant})$$

The spectral magnitude for each frequency was computed by taking the square root of the sum of squared beta coefficients of sine and cosine predictors:

(Formula 3.7) $$\text{Spectral magnitude} = \text{sqrt}(\text{sine coef}^2 + \text{cosine coef}^2)$$

Statistical significance of the spectral magnitude was determined by comparing the spectral magnitude of the empirical data with the 95th percentile of a permutation distribution, which was generated by shuffling the original behavioural/neural time course and performing the same analysis 5,000 times.

To test whether the sensitivity and spectral amplitude of the distractor-evoked ERP at 25 Hz are co-modulated, for each participant, cross-correlation coefficients across time lags of the two signals were obtained (using the “xcorr” function on z-scored time courses in Matlab). Again, we ran a similar linear mixed model as explained above, but this time with sine- and cosine-transformed time lags as predictors and used the correlation coefficients from the cross-correlation as the outcome measure. The spectral magnitude was obtained using formula 3.7 and statistical significance with the same permutation method mentioned above.

3.2.7 Phasic modulation of behavioural sensitivity

To explore the role of pre-distractor neural dynamics on pitch discrimination performance, we examined whether the pre-distractor oscillatory phase relates to behavioural sensitivity. To this end, we examined the quadratic fit of sensitivity as a function of neural phase in source space.

First, we implemented the source analysis using the Fieldtrip toolbox. First, a standard volume conduction model and standard electrode locations were used to calculate the leadfield matrix with 10-mm resolution. We applied the linearly constrained minimum variance (Van Veen et al., 1997) (LCMV) beamformer approach on the 10 Hz lowpass filtered data centred around distractor onset (-1 to 1s). We calculated a common filter including all trials by calculating the covariance matrix estimates. There were in total 2,015 source locations inside the brain.

Second, a quadratic fit analysis resolved by frequency and time probed the spectral and temporal specificity of the phasic modulation of perceptual sensitivity. To obtain trial-wise phase values for each source location, the following procedure was implemented for each trial in each source location: First, the single-trial EEG time course was projected into the source space using the common filter. Then, a sliding window (0.4s duration; moving in 50-ms steps from –0.3 to +0.3s relative to distractor onset) was employed to transform the data into the frequency domain (using FFT). Note that the time point of the sliding window refers to the mid-point of each time window. For instance, the time window centred at -0.3 included data from -0.5 to -0.1 s. The respective phase value of each frequency (2.5 – 8 Hz in 0.5-Hz steps) was then calculated using the *angle* function in MATLAB. The phase values of all trials were binned into 9 bins of equal size, ranging from -pi to pi, followed by a calculation of sensitivity for each bin. The quadratic fit of sensitivity across phase bins was estimated using the *polyfit* function (order = 2) in MATLAB. As a result, we obtained a quadratic fit index for each source location, frequency, and time of interest.

We used a source-level cluster-based permutation test (Maris & Oostenveld, 2007) to find significant clusters in voxel-frequency-time space that would exhibit phasic modulation of sensitivity. Dependent-samples t-tests were used to contrast quadratic fit coefficients against zero, followed by clustering of adjacent bins with significant effects in voxel-frequency-time space. To derive cluster p-values, summed t-values in observed clusters were tested against 5,000 permutations with shuffled condition labels (two-tailed).

To demonstrate that the significant cluster found in the above analysis does not primarily originate from the auditory cortex, we localised, for comparison, the distractor-evoked inter-trial phase coherence (ITPC) at 3 – 7 Hz, strongly assumed to emerge at least to large degrees from the supratemporal plane and auditory cortex (Koerner & Zhang, 2015; Mayhew et al., 2010; Oya et al., 2018), with the following procedure for each voxel: For each trial, we projected the time series EEG data into source space using the same common filter as in the analysis on the phasic relationship with behaviour. Then, we transformed the source-projected data (0 – 300 ms after distractor onset) to the frequency domain using FFT. The same calculation as on the sensor level was used to calculate the ITPC for each frequency. ITPC across frequencies 3 – 7 Hz were then averaged to obtain one distractor-evoked ITPC value for each voxel.

3.3 Results

In the current electroencephalography (EEG) and behavioural study, we aimed at (1) uncovering the temporal fluctuations in distraction, and (2) exploring the relationship between such fluctuations and momentary neural phase at similar frequencies. To this end, we varied the onset time of an auditory distractor that was presented in-between two to-be-compared tones in a variant of a pitch discrimination task.

We probed this research question in the auditory modality as temporal information is especially important to auditory attentional selection (Shamma et al., 2011). During the task, participants (N = 30) had to identify whether the two target tones were the same or different in pitch (Figure 3.1A). The distractor was a fast-varying, 25-Hz modulated sequence of tones that differed in pitch, which allowed us to extract its induced 25-Hz neural response (Ding & Simon, 2009).

Distractors were present in half of the trials and absent in the remaining trials. In distractor-present trials, the distractor onset was uniformly distributed across 24 onset times (0 – 1.15 s, in 0.05 s steps, after tone 1 offset). In distractor-absent trials, no distractor was presented between the two tones. The inclusion of distractor-absent trials serves two purposes. First, we could verify that the distractors had the potency to distract by comparing behavioural performance for distractor-present versus distractor-absent trials (Wöstmann et al., 2022). Second, participants could not anticipate whether or when a distractor would occur in a given trial, which eliminated potential effects of such anticipation on behavioural performance (Grabenhorst et al., 2021) or pre-stimulus neural activity (Dürschmid et al., 2018; Herbst et al., 2022; Stefanics et al., 2010).

3.3.1 Distractors interfere with pitch discrimination performance

To examine the potency of the distractors to distract, we compared participants' sensitivity and criterion (response bias) of the pitch discrimination task between distractor-present and -absent trials. Participants were less sensitive to the pitch difference (t_{29} = -8.11, p = <.001, Cohen's d = -1.48), and had a more conservative response criterion (i.e., more "same pitch" responses; t_{29} = 2.83, p = .008, Cohen's d = 0.52) on distractor-present trials (Figure 3.1B).

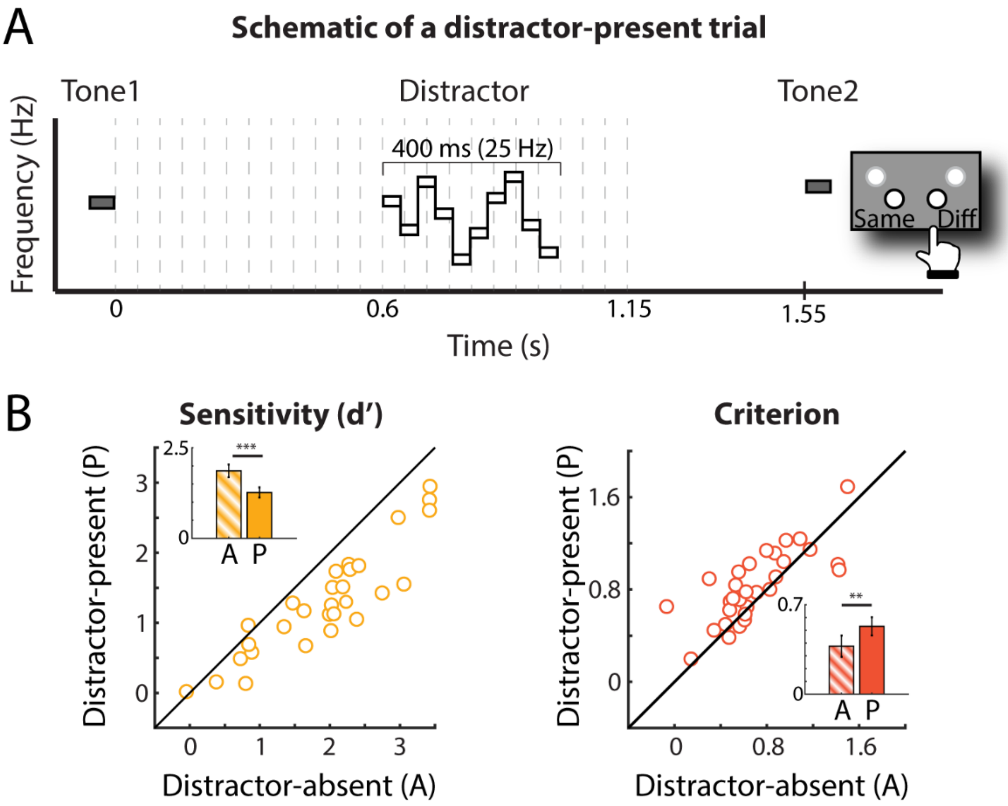

Figure 3.1. A) Schematic of a distractor-present trial. Participants were instructed to indicate whether the two target tones (grey) were the same (probability = 50%) or different (higher, probability = 25%; or lower, probability = 25%) in pitch. A 10-tone-pip distractor sequence (white) with a 25-Hz temporal structure (i.e., 40-ms tone-pip duration; total duration 400 ms) was presented at one of the 24 distractor onset times (dashed lines). In distractor-absent trials, no distractor was presented. B) Behavioural results comparing distractor-present and -absent conditions. Coloured circles indicate single-subject data. Insets show bar graphs of perceptual sensitivity (left panel) and criterion (right panel) for distractor-present (solid bar) and distractor-absent (gradient bar) conditions, respectively. Error bars show ±1 SEM. ** p < .01. *** p < .001.

3.3.2 Behavioural and neural measures of distraction co-fluctuate across time

Does the impact of distraction on neural activity and goal-directed behaviour exhibit fluctuations across time? To test this, we varied distractor onset time and examined whether behavioural and neural measures of distraction would show modulations at frequencies up to 8 Hz. Behaviourally, perceptual sensitivity was calculated as an indirect measure of distraction: The more distracted, the lower the sensitivity in pitch discrimination should be (Figure 3.2A, yellow, see Figure S3.1 for individual participants' time courses). Neurally, we calculated the distractor-evoked event-related potential (ERP; Figure 3.2B) for each distractor onset time and used a fast Fourier transform (FFT) to extract its amplitude at 25 Hz, which corresponded to the modulation rate of the frequency-modulated distractor tone sequence (Figure 3.2A, blue, see Figure S3.1 for individual participants' time courses).

To examine temporal fluctuations of distraction, we used linear mixed-effects models with sine- and cosine- transformed distractor onset time as predictors to model behavioural (i.e., perceptual sensitivity) and neural (i.e., distractor-evoked ERP) time courses as the outcome measures. This method outperforms other methods for studying the phasic modulation of behavioural and neural responses (Zoefel et al., 2019) and has also been used previously (Wöstmann et al., 2020) to extract temporal fluctuations in the vulnerability of working memory to distraction. A quadratic trend was observed in the behavioural time course in Figure 3.2A as the earliest and latest distractors were most distracting due to their temporal proximity to the target tones. Before running linear mixed models, we removed the quadratic trends in the two measures as they were not of interest in the current study (Huang et al., 2015).

Figure 3.2E and F show the spectral magnitude (0.5–8 Hz, 0.5-Hz steps) resulting from linear mixed models on detrended perceptual sensitivity (Figure 3.2C, yellow) and detrended ERP amplitude (Figure 3.2C, blue), respectively. Statistical significance was derived by testing empirical spectral magnitude against the 95^{th} percentile of a permutation distribution, which was derived from shuffling the behavioural and neural time courses, respectively, 5,000 times (see Methods for details).

At the behavioural level, distractor onset time modulated sensitivity below 5 Hz. At the neural level, distractor onset time modulated the distractor-evoked ERP at 4 and 5 Hz. Similar results were obtained in a control analysis, where temporal fluctuations in sensitivity in distractor-present trials were compared against distractor-absent trials (instead of permuted distractor-present trials; Figure S3.3).

If these periodic neural dynamics serve as the basis for the apparent behavioural fluctuations, we should observe the synchronization of the behavioural and neural time courses by a common rhythm. To test this, we also examined the co-modulation of sensitivity and distractor-evoked ERP by distractor onset time. We first calculated the cross-correlation coefficients of the behavioural and neural time courses for individual participants (Figure 3.2D). We then ran a linear mixed model with the cross-correlation coefficient as the outcome measure and sine- and cosine-transformed time lag as predictors.

Figure 3.2G shows that sensitivity and distractor-evoked ERP are co-modulated at 3.5 and 5 Hz. At lag 0, there was a negative correlation between sensitivity and the distractor-

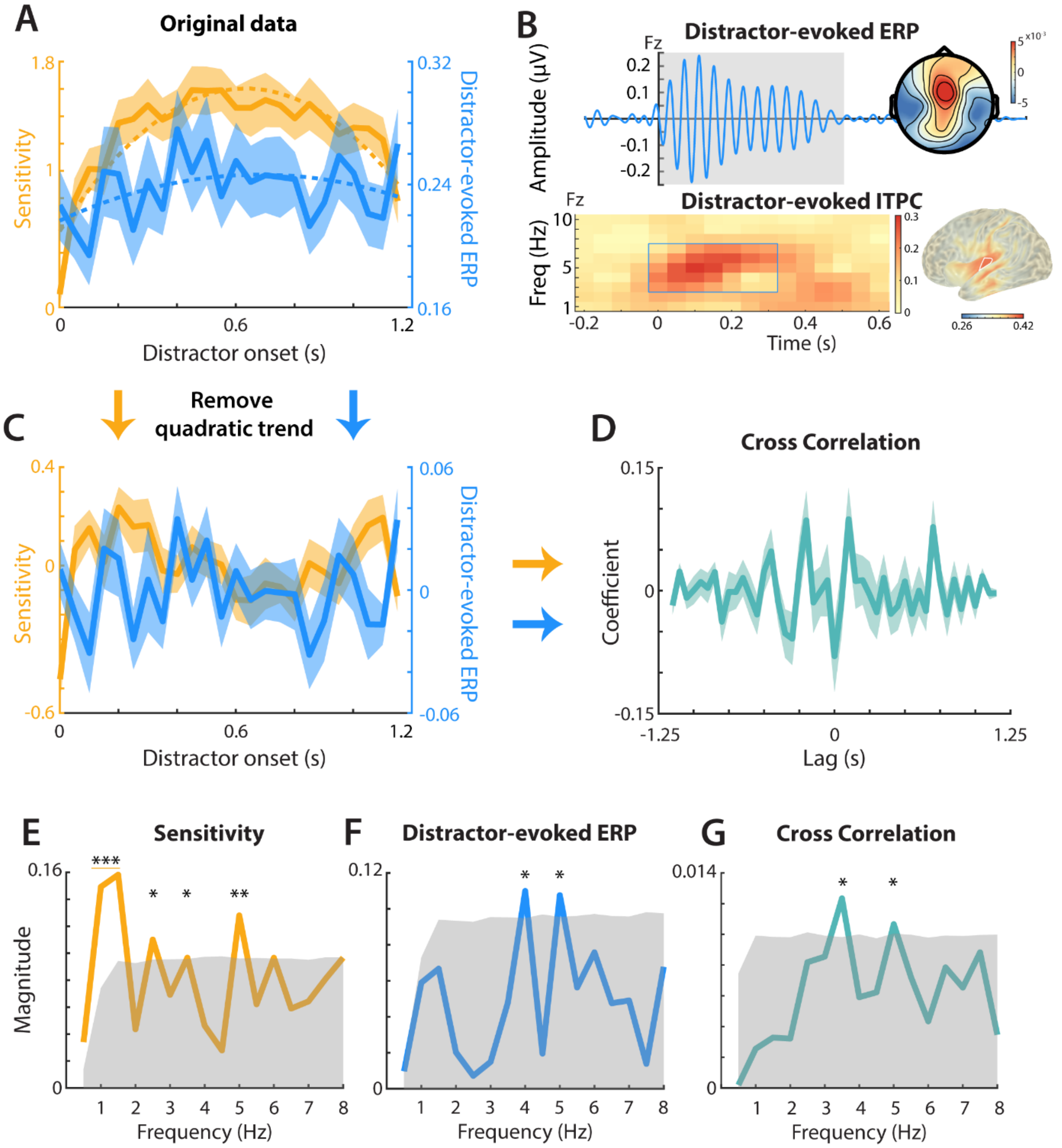

Figure 3.2. A) Average sensitivity (yellow solid line) and 25-Hz amplitude of the distractor-evoked event-related potential (ERP; blue solid line) across distractor onset times. Shaded areas show ±1 SEM across participants. Dashed lines show respective quadratic trends. B) Top panel: Distractor-evoked ERP waveform averaged across all distractor onset times at electrode Fz (20 – 30 Hz bandpass filtered for visualization purpose). The shaded grey area marks the time window used to extract the 25-Hz amplitude of the distractor-evoked ERP. The inset shows the scalp map of the 25-Hz amplitude of the distractor-evoked ERP (derived via an FFT on the distractor-evoked ERP waveform). Bottom panel: Distractor-evoked inter-trial phase coherence (ITPC) from 1 – 10 Hz and -0.2 s – 0.6 s at Fz. Brain surface shows the ITPC values (frequencies: 3 – 7 Hz; time window: 0 – 0.3 s) in source space, which reflects the auditory response to the distractor. The white outline indicates the top 1% voxels with the largest ITPC values. C) Detrended time courses of behavioural and neural outcome measures. Shaded areas show ±1 SEM across participants. D) Solid line shows average correlation coefficients, derived by averaging single-subject cross-correlations of sensitivity and distractor-evoked ERP time courses, as a function of temporal lags. The shaded area shows ±1 SEM across participants. E-G) Spectral magnitude across frequencies (0.5 – 8 Hz, 0.5-Hz step) for (E) detrended sensitivity, (F) distractor-evoked ERP, and (G) the cross-correlation between the two. Shaded areas show the 95th percentile of the permutation distribution generated from 5,000 permutations. * $p < .05$. ** $p < .01$. (uncorrected)

evoked ERP, consistent with the notion that stronger distractor encoding (i.e., larger distractor-evoked ERP) corresponds to worse task performance (i.e., lower sensitivity). T-tests against zero on the (Fisher-z transformed) correlation coefficients across participants show that this correlation at time lag 0 was close to statistical significance (Pearson's r: $t_{29} = -1.85$, $p = 0.08$, mean Pearson's $r = -0.08$; Spearman's r: $t_{29} = -2.13$, $p = 0.04$, mean Spearman's $r = -0.10$).

As a control analysis, the same analysis pipeline was run on the data in the distractor-absent condition by randomly assigning a "distractor onset" for each distractor-absent trial, which did not reveal any significant co-modulation (Figure S3.4): Neither time courses of sensitivity nor distractor-evoked ERP were modulated by distractor onset time; time lags did not modulate the cross-correlation of these two at any frequency. The temporal co-fluctuations of behavioural and neural measures of distraction at 3 – 5 Hz in distractor-present trials may be a manifestation of an underlying distractibility rhythm, which we probed into next.

3.3.3 Pre-distractor neural phase in the inferior frontal/insular cortex explains the distraction

If the human brain hosts an endogenous rhythm that underlies distractibility dynamics, the neural state prior to distractor onset should explain the participant's momentary vulnerability to interference by a distractor. To test this, we studied how the pre-distractor neural phase relates to our previously established proxy of distraction, that is, behavioural sensitivity. We asked when in time and in which brain network(s) such an endogenous rhythm underlying distractibility would show up.

We employed source-projected EEG time courses to extract the quadratic relationship between the binned pre-distractor neural phase and perceptual sensitivity. For each trial (Figure 3.3A), we first transformed a source-projected EEG data segment (0.4 s; sliding window) into the frequency domain using FFT. We then extracted the neural phase for a given frequency (Figure 3.3B). To calculate sensitivity sorted by phase bin, we first sorted the trials according to their phase values into 9 phase bins of equal size, followed by the calculation of perceptual sensitivity for each bin (see Figure S3.5 for individual participants' sensitivity by phase bin). The same procedure was repeated for a range of frequencies (2.5 – 8 Hz, 0.5-Hz steps) and time windows (-0.3 – 0.3 s around distractor onset, 0.05-s steps). A cluster-based permutation test with the dimensions time, frequency, and voxels, wherein the quadratic fit was tested against zero, revealed a positive significant cluster (Figure 3.3C; the same analyses with 7, 8, and 10 phase bins yielded comparable clusters across all dimensions and comparable statistical significance). The quadratic modulation of sensitivity by neural phase at 2.5 – 7.5 Hz was most prominent in the left insular and the inferior frontal cortices in the time window spanning ~300 ms before distractor onset (cluster p-value = .026, two-tailed; see Figure S6 for brain surface plots from other viewing angles).

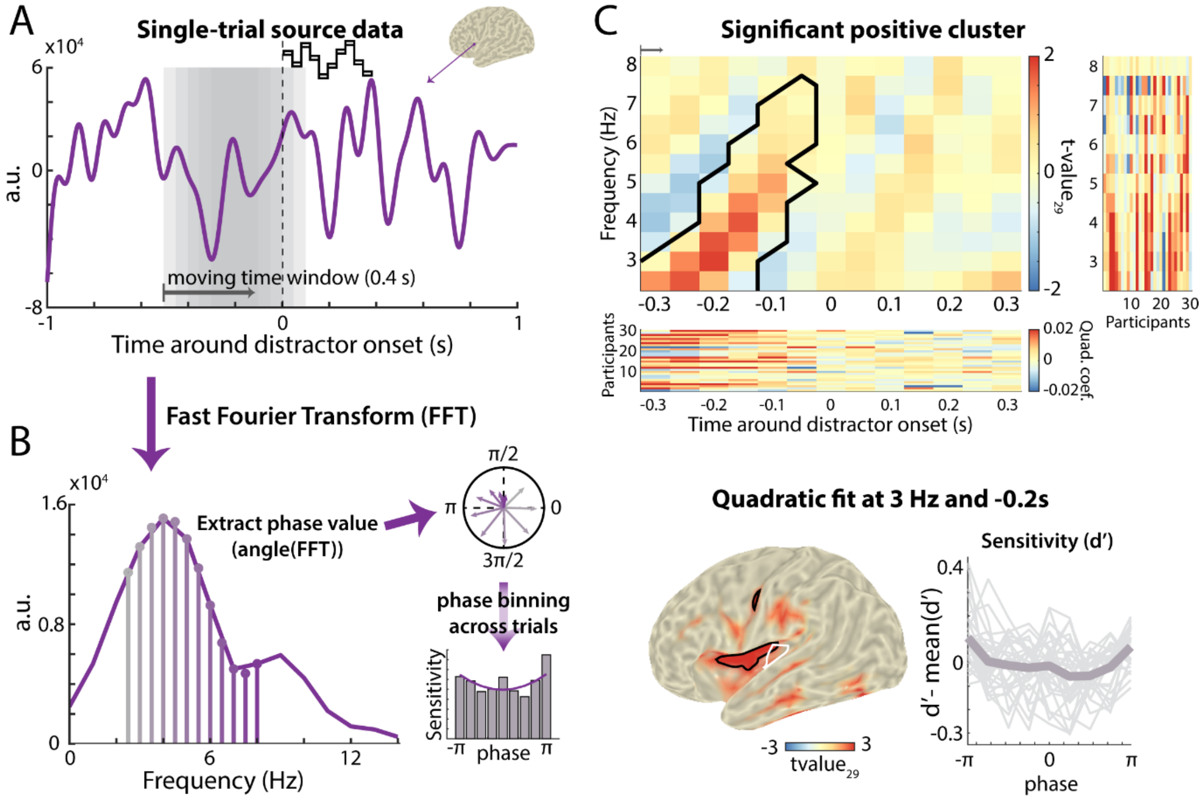

Figure 3.3. A-B) Illustration of the source-level analysis. A) Example of a single-trial source-projected EEG time course. The moving window (grey) was used to transform segments of the data into the frequency domain using FFT. The first grey window corresponds to the first time window used in the time-resolved analysis (i.e., -0.5 to -0.1 s). B) Spectral representation of the data segment in (A). Phase values across frequencies were extracted and trials were binned according to their phase values into 9 phase bins for each frequency, time window, and source location. The bar graph shows exemplary sensitivity values calculated from the trials sorted by phase bin. A quadratic trend was fitted to the sensitivity values across phase bins (purple solid line). C) Results of a cluster-based permutation test, which tested quadratic fits in time-frequency-source space against zero. The top panel shows the t-values (df = 29) across frequencies and time windows, averaged across all the voxels belonging to the significant positive cluster. The black contour indicates the positive significant cluster. The right column shows individual participants' quadratic coefficients for each frequency, collapsed across the time windows included in the significant cluster. The bottom row shows individual participants' quadratic coefficients across time windows, collapsed across frequencies and voxels included in the significant cluster. The bottom left panel shows the cluster peak effect (3 Hz; -0.2 s), which resides mainly in the left inferior frontal cortex and insular cortex. Only the t-values of the positive significant cluster are shown. The black contour indicates the regions with the top 1% t-values across the whole brain. The t-values were interpolated and projected onto MNI coordinates for visualization purposes. The white contour indicates distractor-evoked neural activity, quantified as the top 1% inter-trial phase coherence (ITPC) in the post-distractor time window (i.e., 0 – 0.3 s) at 3 – 7 Hz (shown also in Figure 2B). The bottom right panel shows centred perceptual sensitivity sorted by phase bins in the positive cluster at 3 Hz averaged across participants. Grey thin lines show individual centred perceptual sensitivity.

To test whether the significant cluster overlaps with sources of auditory-evoked activity in auditory cortex regions, we compared its source with the source of distractor-evoked inter-trial phase coherence (ITPC) at 3 – 7 Hz (shown also in Figure 3.2B, bottom panel). Importantly, although the two effects were localized in proximal cortical regions (Figure 3.3C, bottom panel), their core regions were mostly non-overlapping.

For control, we conducted the same analysis on the distractor-absent trials, which revealed no significant cluster (Figure S3.7). We also tested the relationship between the pre-distractor neural phase and the post-distractor neural measure of distraction (i.e., 25-Hz amplitude of the distractor-evoked ERP), which did not reveal a significant effect (Figure S3.8).

3.4 Discussion

The current study aimed to unravel the temporal dynamics of distractibility, using a pitch discrimination task with auditory distractors. The eventual degree of distraction and the neural processing of distractors were respectively quantified by distractor-evoked performance detriments and neural responses in the human electroencephalogram (EEG). We made a series of interesting observations.

First, the ~3 – 5 Hz fluctuations of behavioural sensitivity across distractor onset time urged for the question of whether the same fluctuations are observed in the human brain's response to distractors. Consistently, we found that the distractor-evoked neural response covaries with behavioural sensitivity at similar frequencies. Second, while behavioural sensitivity and the distractor-evoked neural response might partly reflect post-perceptual processes (such as distractor suppression), we asked whether the brain hosts an endogenous oscillation that shapes the momentary state of distractibility. Confirming this, we found that the pre-distractor neural phase in the left inferior frontal/insular cortex explained rhythmic fluctuations in the momentary degree of distraction.

These major findings support the notion that temporal fluctuations in distractibility on a subsecond time scale can be explained by slow neural oscillatory dynamics in a cortical network beyond the auditory cortex.

3.4.1 The proneness to distraction is inherently dynamic

The current study sheds light on the dynamics of distractibility, which is an important factor often neglected in previous attention research on distraction and suppression. The ultimate degree of detriment that a distractor will cause depends on two endogenous factors: the momentary proneness to distraction (i.e., distractibility) and the ability to suppress a distractor (i.e., distractor suppression). On the one hand, research on distractor suppression often did not disentangle the active suppression of distractors (Schneider et al., 2021) from variations in distractibility. On the other hand, research on distractibility rather treated it as an individual characteristic that, if at all, only changes on a slow temporal scale such as within an experimental session (Forster & Lavie, 2014) or across developmental stages (Kannass et al., 2006). The temporal trajectory of distractibility on a faster, subsecond, time scale had hitherto been left unknown.

With distractor-evoked behavioural and neural measures, we were able to encapsulate the temporal trajectory of distraction, which fluctuates on a subsecond temporal scale consistent with the rate of rhythmic sampling in attention (Fiebelkorn et al., 2013; Ho et al., 2017; Kubetschek & Kayser, 2021; Landau & Fries, 2012) and working memory (Cruzat et al., 2021; Schmid et al., 2022; ter Wal et al., 2021). With analysis of the pre-distractor neural oscillatory phase, we were able to trace this distractibility back to a slow neural oscillatory fluctuation in the inferior frontal and insular cortex (see below for an in-depth discussion). Participants could not anticipate whether or when the distractor would occur, thereby not being able to engage in preparatory suppression of the upcoming distractor (Geng, 2014). The combined analysis of the pre-distractor neural phase and post-distractor neural and behavioural measures complementarily elucidates how the brain alternates between states of higher and lower distractibility. These insights are essential for the inclusion of an explicit account of distraction in models of attention in psychology and neuroscience.

Fluctuations of distractibility at 3 – 5 Hz in the current study unveil the dynamic nature of attention, which was underappreciated in the static spotlight metaphor of attention (M. I. Posner et al., 1980). The attentional sampling of the to-be-attended external stimuli (Fiebelkorn et al., 2013; Ho et al., 2017; Kubetschek & Kayser, 2021) or internal memory representation (Cruzat et al., 2021; Schmid et al., 2022; ter Wal et al., 2021) has been shown to exhibit temporal fluctuations at similar frequencies. The waxing and waning of attentional sampling may index inter-areal coordination between the attentional network and the sensory areas of the brain (Dugué & VanRullen, 2017), which is associated with the alternation between stronger and weaker attentional sampling over time (Fiebelkorn & Kastner, 2019). With much evidence on the temporally dynamic nature of the attentional spotlight, however, there is a lack of theoretical foundation for the inherent dynamics of cognition outside of this spotlight (Lui & Wöstmann, 2022). With the observed fluctuations of distractibility in the theta frequency range, an extension of the existing theory of dynamic attentional sampling to temporally dynamic distraction is warranted.

While our results demonstrate that distractibility exhibits temporal fluctuations, they do not reveal whether such fluctuations are independent of the fluctuations found in the attentional sampling of memory content. Participants in the current study had to maintain the memory representation of the pitch of tone 1 during a trial. The theta fluctuations found in the current study thus may represent the sampling of the internal representation of tone 1, with higher distractibility hypothetically occurring during the phase of reduced sampling of the memory representation. Alternatively, observed theta fluctuations may represent independent fluctuations in the proneness to distraction. Previous neuroimaging studies found that the suppression of distracting inputs may be independent of the sampling of attended inputs (Noonan et al., 2016; Schneider et al., 2018; Wöstmann et al., 2019). Future investigations may manipulate both the target and distractor onset time to examine the relationship between the temporal fluctuations underlying attentional sampling and distractibility.

Of note, as the main analysis approach used here (comparing empirical time courses to time courses that were shuffled in time) does not distinguish between periodic and aperiodic temporal structure (Brookshire, 2022), we are careful to conclude from the respective results alone that distractibility is rhythmic. However, it does not negate the possibility that there is a periodic temporal structure in distractibility. The premise of rhythmic cognition is that the apparent fluctuations of performance reflect the periodic orchestration between brain regions (Fiebelkorn & Kastner, 2019). In addition to fluctuations in behavioural performance, neural evidence is, therefore, essential to elucidate the rhythmicity of cognition (Fiebelkorn, 2022; Wöstmann, 2022). The current study shows a correspondence between slow neural oscillatory phase and behaviour (using an analysis approach that does not employ shuffling-in-time), consistent with the notion that distractibility is rhythmic. Future advancements in the analysis approach to directly test the periodicity in cognition will further strengthen our understanding of the distractibility dynamics.

3.4.2 Neural dynamics of distractibility originate in inferior frontal/insular cortices

The localisation of neural phase effects underlying distractibility dynamics beyond auditory cortex regions might suggest that the proneness to distraction is supra-modal. In research on visual distraction, brain regions in frontal and parietal cortices have been associated with distractor interference in lesions (Chao & Knight, 1995) or transcranial magnetic stimulation (Kanai et al., 2011; Wais et al., 2012) studies. The functional connectivity between the left inferior frontal cortex and hippocampus is associated with the disruptive influence of task-irrelevant visual distraction on working memory (Wais et al., 2010). While the current study examined distractibility in the auditory modality, the neural origins found here overlap with previous research on distraction in the visual modality.

The observed relationship between perceptual sensitivity and the inferior frontal/insular theta phase suggests that fluctuations in distractibility may be related to the cognitive control of working memory. The left inferior frontal cortex is assumed to be critical to the resolution of competition between the maintenance of goal-relevant information and the interference from the external distraction (Irlbacher et al., 2014; Tops & Boksem, 2011; Wais et al., 2012). The anterior insula is theorised as a gatekeeper to the brain regions responsible for the goal-related cognitive control (Molnar-Szakacs & Uddin, 2022), and is part of the ventral attention system (Eckert et al., 2009). Specifically, the insular cortex may support the switching between networks important to internally directed and externally directed cognition, respectively (Uddin, 2015). The frontal theta rhythm is associated with cognitive control (B. Berger et al., 2019; Cavanagh & Frank, 2014; Kamarajan et al., 2004) and the prioritization of the relevant memory representation (Riddle et al., 2020). Taken together, theta oscillations in the inferior frontal and insular cortices may reflect the orchestration of the cognitive control system to maintain the internal memory representation and suppress potentially distracting external inputs.

Against what might have been expected, the pre-distractor neural phase did not predict fluctuations in the distractor-evoked neural response (Figure S3.8). However, this null result might rest on the distractor-evoked ERP being a rather unspecific proxy of distraction. Components of the distractor-evoked ERP have been shown to reflect cognitive operations other than distraction, such as the reactive suppression (Feldmann-Wüstefeld & Vogel, 2019; Hickey et al., 2009; B. Wang et al., 2019) or stimulus prediction (Volosin & Horváth, 2014). Distractibility dynamics may only account for a small amount of variance in the distractor-evoked ERP.

3.5 Conclusion

The present study demonstrates that human proneness to distraction is not uniformly distributed across time but fluctuates on a subsecond timescale in cycles of ~3 – 5 Hz. In the brain, time windows of higher distractibility are coined by stronger neural responses to distractors. Furthermore, the slow neural phase in the left inferior frontal/insular cortex regions explains fluctuations in distractibility. These results unravel the temporal dynamics of distractibility and thereby help explain human processing of an abundant kind of stimulus in increasingly complex environments, that is, irrelevant and distracting input.

3.6 Supplementary information

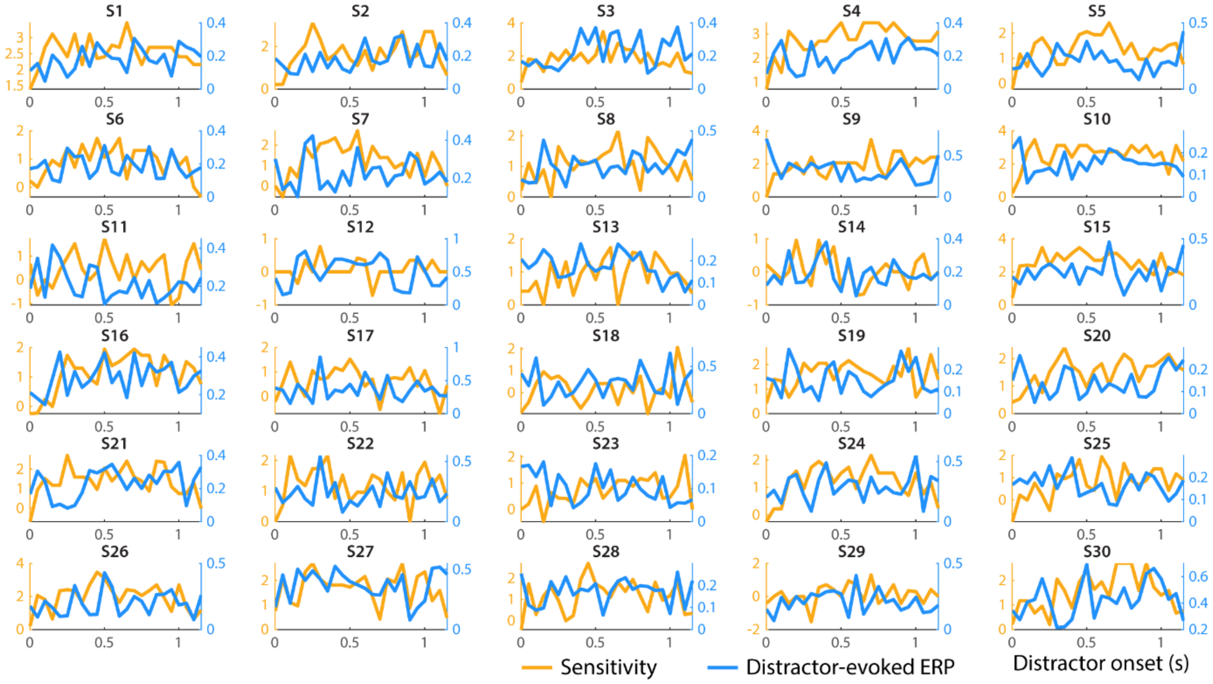

Figure S3.1. Time courses of raw sensitivity (yellow) and distractor-evoked ERP (25-Hz amplitude of distractor-evoked ERP; blue) for each individual participant.

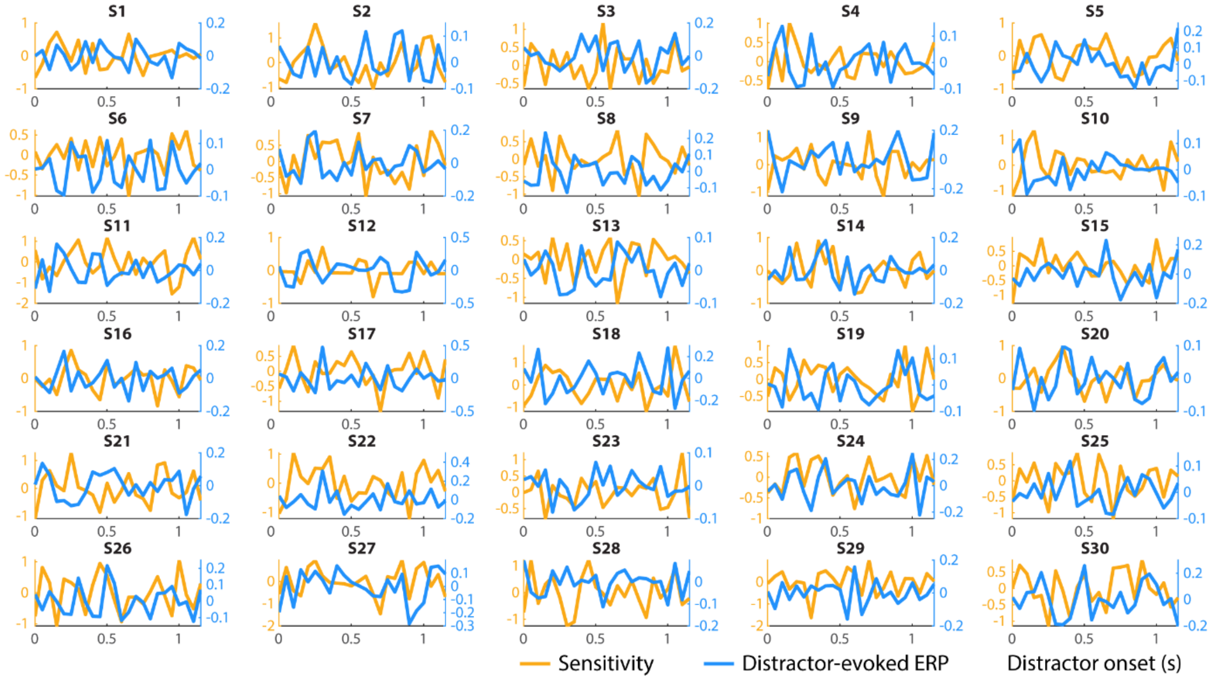

Figure S3.2. Detrended (quadratic trend removed) sensitivity (yellow) and distractor-evoked ERP (blue) time courses for each individual participant.

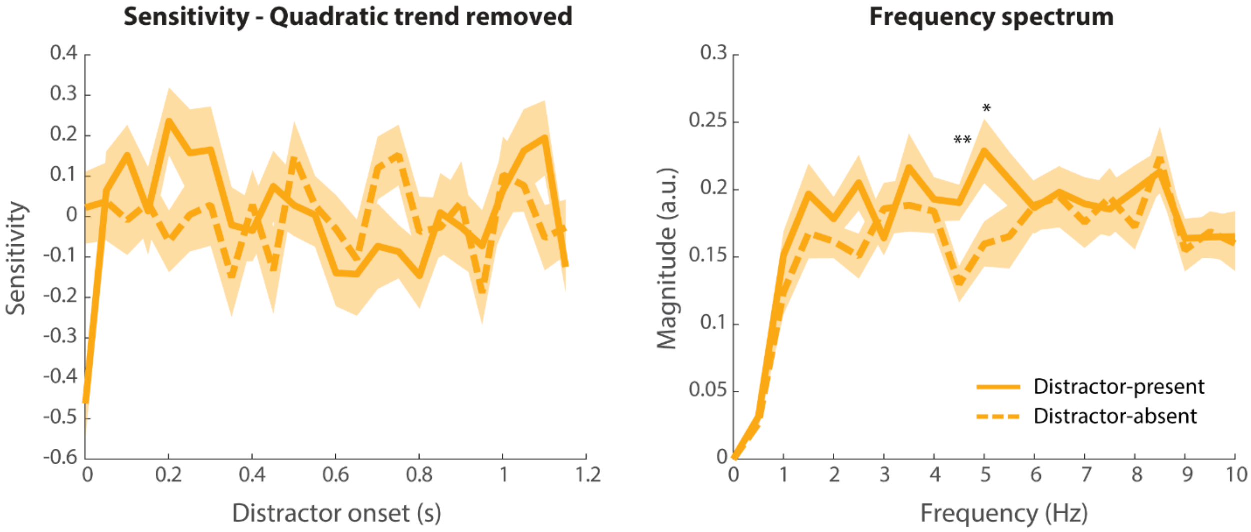

Figure S3.3. The left panel shows the sensitivity time courses for distractor-present (solid) and distractor-absent (dashed) conditions. The right panel shows the averaged frequency spectra, derived from FFT on single-subject time courses. Shaded areas show ±1 SEM across individual participants. Asterisks show statistical significance when comparing the spectral magnitude of distractor-present versus -absent conditions (using uncorrected dependent-samples t-tests). * $p < .05$ ** $p < .01$

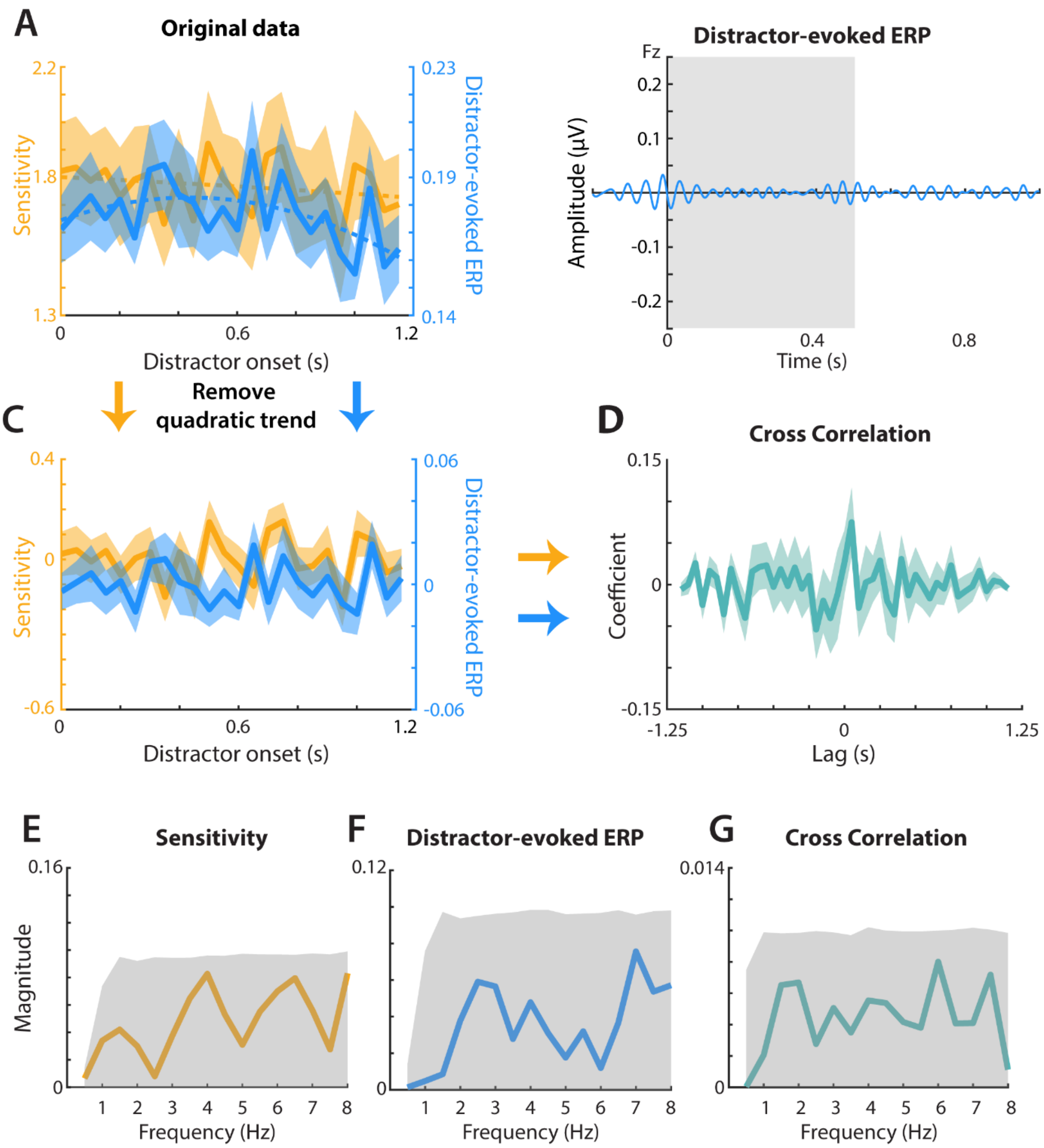

Figure S3.4. The same analysis pipeline as shown in Figure 3.2, applied here to the distractor-absent condition.

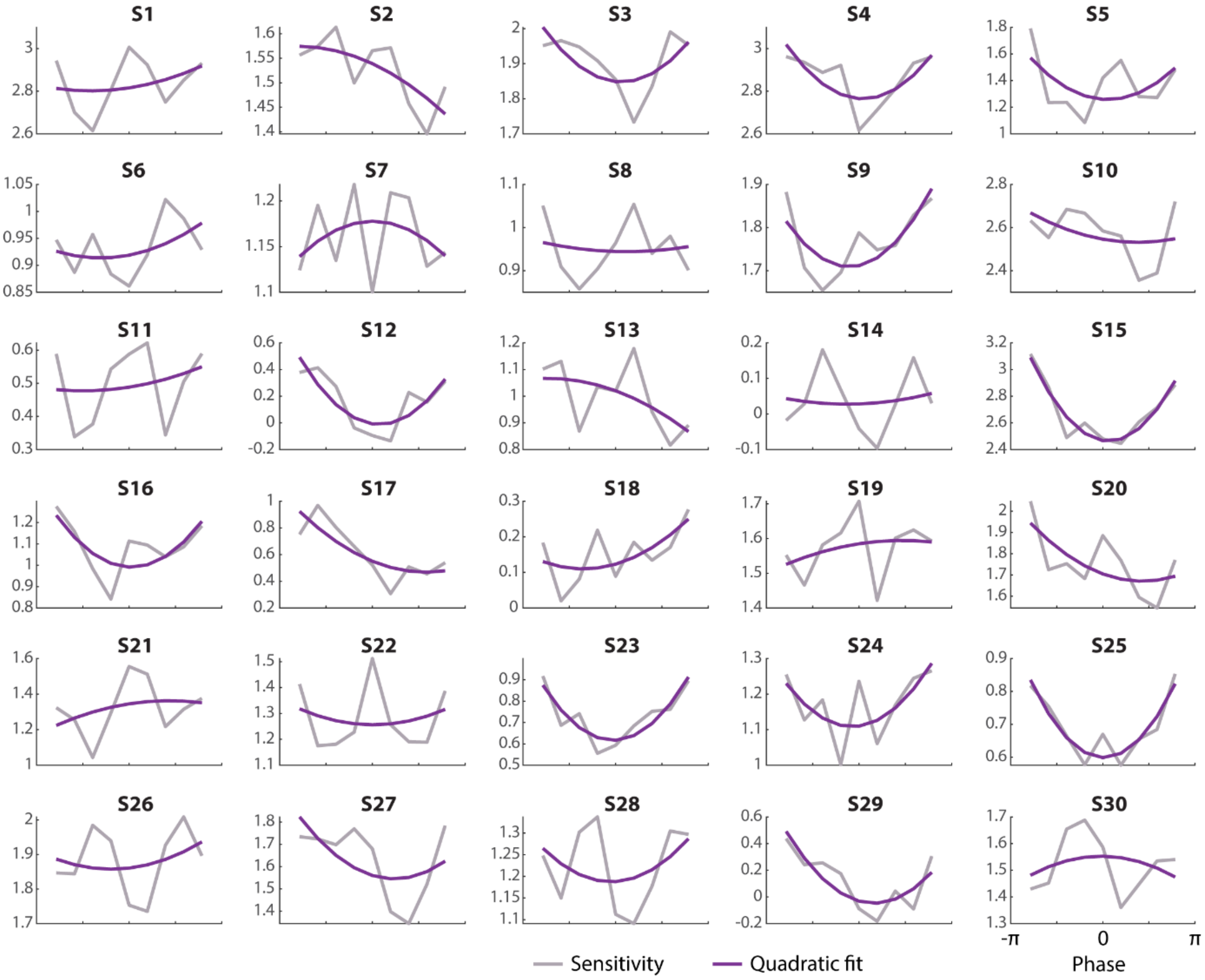

Figure S3.5. Individual sensitivity (grey line) and quadratic fit (purple line) across phase bins of the significant positive cluster at 3 Hz.

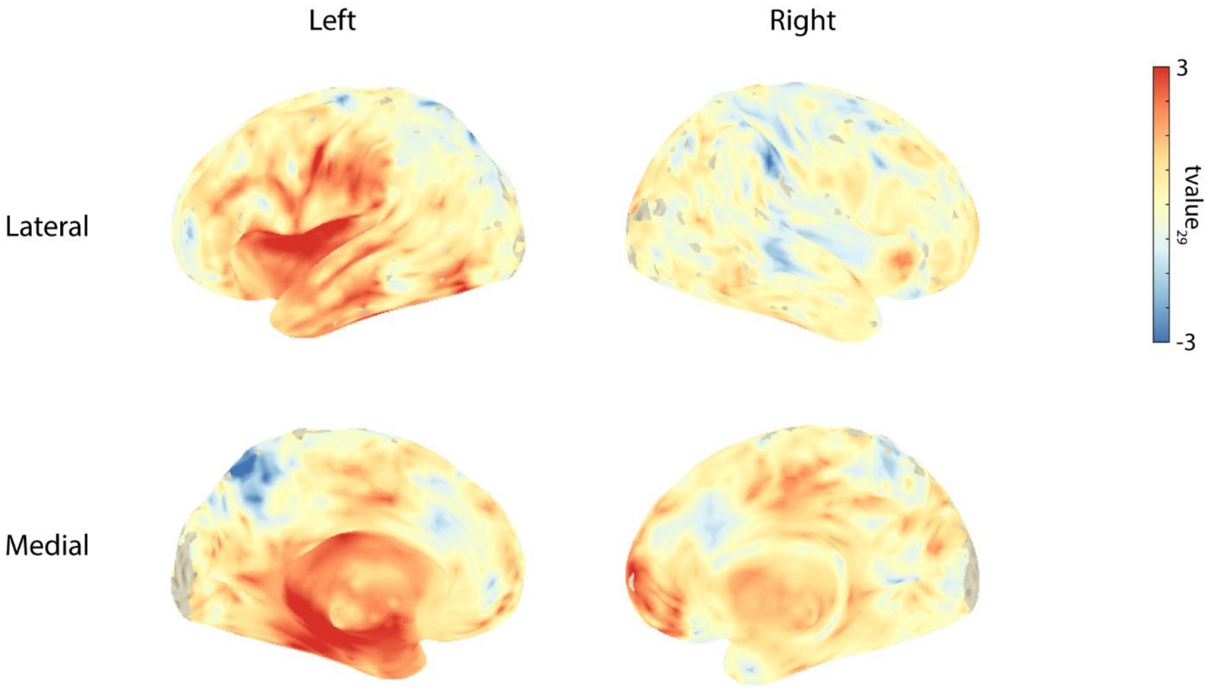

Figure S3.6. Brain surface plots of the cluster peak effect (3 Hz; -0.2 s) from left lateral (top left), right lateral (top right), left medial (bottom left), and right medial (bottom right) views show t-values for the comparison of the quadratic fit of the sensitivity sorted by phase bins against zero. The t-values were interpolated and projected onto MNI coordinates for visualization purposes.

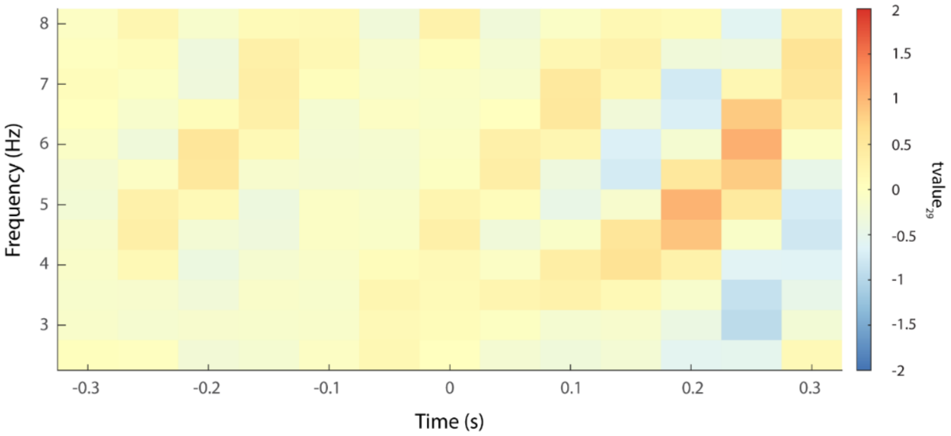

Figure S3.7. Results of the cluster-based permutation test, across time windows and frequencies, on the quadratic relationship between neural phase and sensitivity for the distractor-absent condition. The figure shows t-values (df = 29) averaged across all the voxels belonging to the significant positive cluster in the distractor-present condition shown in Figure 3.3. No significant cluster was found in the distractor-absent condition.

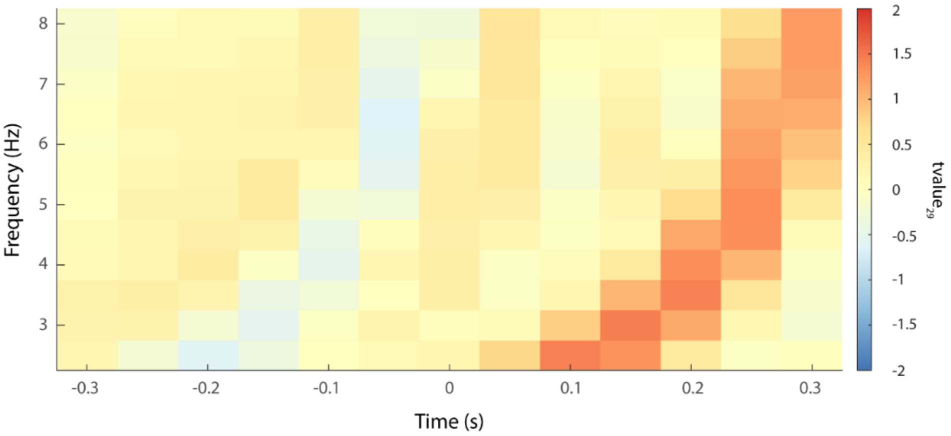

Figure S3.8. Results of the cluster-based permutation test, across time windows and frequencies, on the quadratic relationship between neural phase and distractor-evoked ERP amplitude at 25 Hz. The figure shows t-values (df = 29) averaged across all the voxels belonging to the significant positive cluster testing the quadratic relationship between neural phase and behavioural sensitivity shown in Figure 3.3. As expected, and not of main interest in the current study, a significant cluster in the post-stimulus time window (i.e., >0s) was found. More importantly, no significant cluster was found in the pre-distractor time window (i.e., <0 s).

4 Study 2: Effects of temporally regular versus irregular distractors on goal-directed cognition and behaviour[2]

4.1 Introduction

Sensory events in human environments often possess an inherent temporal structure (e.g., a ticking clock in the living room). Some of these events are relevant for goal-directed behaviour, while others are irrelevant and potentially distracting. Dynamic attending theory (Large & Jones, 1999) suggests that temporal regularity of task-relevant stimuli guides attentional resources to the expected onsets of stimuli, and hence facilitates sensory processing at these time points. The prevalence of temporal regularity in task-irrelevant stimuli urges the question of whether temporal regularity of distraction impacts humans' execution of goal-directed cognitive operations.

Shielding memory representation against external distraction is important to successfully maintain relevant information (Lorenc et al., 2021; Oberauer, 2019). The irrelevant-sound task (Colle & Welsh, 1976; Salamé & Baddeley, 1982), in which participants need to maintain the order of target numbers in memory while ignoring auditory distractors, provides a gateway to probe how different psycho-acoustic features of distractors interfere with working memory. The irrelevant-sound effect refers to the observation that, compared with stationary background noise or silence, memory interference is larger for irrelevant sounds, such as speech distractors (e.g., Buchner et al., 2004; Salamé & Baddeley, 1989; Tremblay et al., 2000) or sequences of pure tones with changing frequencies (e.g., D. M. Jones & Macken, 1993; LeCompte et al., 1997), although the size of the irrelevant-sound effect is typically larger for speech versus tone distractors (Ellermeier & Zimmer, 2014; LeCompte et al., 1997). Of relevance to the present study, the degree of interference has also been shown to be modulated by the violation (e.g., Röer et al., 2014), or the lack of (e.g., T. Campbell et al., 2002) repeating structure in the distractor sequence, which could be explained by the auditory deviant hypothesis (Cowan, 1995, 1999) or by the changing-state hypothesis (D. Jones et al., 1992, 1999). Violation of the regular structure of distractor sequences may interfere with working memory by means of attentional capture, which refers to the orientation of attentional resources to a stimulus outside the current focus of attention when the stimulus deviates from expectation (Röer et al., 2014; Schröger & Wolff, 1998). Alternatively, a changing-state distractor (e.g., A-

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C-D-J-E as opposed to A-A-A-A-A) is supposed to interfere with the order of target stimuli maintained in memory in the irrelevant-sound task (T. Campbell et al., 2002; Hughes, Tremblay, et al., 2005).

Given the rich evidence on how different features of distractors interfere with working memory, the paucity of studies on the role of temporal regularity of distractors is surprising. The current study aimed at filling this gap by investigating how the temporal regularity of distractor sequences influences goal-directed working memory. The onset time of distraction has recently been shown to modulate working memory interference (Körner et al., 2019; Wöstmann et al., 2020), demonstrating that temporal features of distractors may play an important role in the susceptibility to distraction in working memory tasks. When it comes to temporal regularity, temporally irregular distractors were recently found to be more disruptive to the detection of deviance in unmasked targets (Makov & Zion Golumbic, 2020). For concurrently presented target and distractor streams, this study supports the view that temporally regular versus irregular distractors differentially interfere with goal-directed cognitive operations. In studies using irrelevant-sound tasks, however, inconsistent results were found, such that participants either performed better (D. M. Jones & Macken, 1995) or worse (Parmentier & Beaman, 2015) with regular versus irregular distractors. It is thus an unresolved question whether and how the temporal regularity of distractors during memory retention affects working memory performance.

Different theoretical accounts may give rise to different predicted effects regarding how the temporal regularity of distractors may disrupt working memory. Within the theoretical framework of the irrelevant-sound effect, previous studies explained the differential effect of isochronous versus random temporal structures on serial memory accuracy based on the changing-state hypothesis. Temporally regular distractor sequences may facilitate (D. M. Jones & Macken, 1995) or interfere with (Parmentier & Beaman, 2015) the perceptual organization of distractors, thereby modulating the precision of the serial memory representation. However, previous evidence also showed that serial order memory depends on the position, rather than the timing, of targets (Gorin, 2020; Ng & Maybery, 2005). Whether a violation of the temporal regularity of distractors acts as a changing-state sequence and influences serial order memory thus remains unclear. Of note, the current study does not strictly test the changing-state hypothesis as the distractors used within each individual experiment were implemented either as a steady-state (in Experiments 1 & 2) or a changing-state (in Experiments 3 & 4) sequence.

Alternatively, according to the auditory deviant hypothesis, temporally regular distractors may facilitate the formation of an expectation regarding when the next distractor may occur. The deviation from temporal regularity may then potentially capture attention, rendering the distractors harder to ignore. Distractor sequences with temporal deviants interfere with the serial recall of concurrently presented to-be-remembered sequences (Hughes, Vachon, et al., 2005). Electrophysiological studies also revealed that the human auditory system detects changes in the temporal regularity of ignored stimuli (Näätänen et al., 1993), which suggests the general potency of temporal (ir)regularity captures attention.

More generally, the temporal regularity of distractors may facilitate or disrupt the shielding of working memory from distractions based on different theoretical considerations. First, some stimulus properties that typically facilitate auditory target processing (e.g., acoustic detail and voice familiarity) were shown to disrupt memory performance when occurring in the distractor (Kreitewolf et al., 2019; Wöstmann & Obleser, 2016). As the temporal regularity of targets typically aids target processing (Morillon et al., 2016; Rohenkohl et al., 2012), temporally regular distractors may in turn be more distracting to the participants. Second, temporal expectation formed by regular temporal structures may decrease the degree of distraction. Previous evidence shows that participants performed better when they had foreknowledge about the deviation in distractors (Hughes et al., 2013), suggesting that expectation may reduce susceptibility to distraction.

The inconsistent evidence in the current body of literature may be due to different reasons, and the current study probed into each of the following conjectures, using a series of experiments. First, the temporal regularity effect may vary depending on the type of temporal (ir)regularity employed. As mentioned, the violation of temporal regularity embedded in the distractor sequence may also potentially capture attention. It is therefore important to test whether deviation from temporal regularity of distractors influences working memory performance. Experiment 1 in the current study investigated the deviant effect in time by manipulating the stimulus onset asynchrony of a final distractor tone in a distractor sequence. Experiment 2 manipulated temporal regularity by using isochronous (regular) versus random (irregular) temporal structure for all items in a distractor sequence.

Second, the modulatory effect of temporal regularity in the distractor sequences on working memory may depend on the type of sound events used in the irrelevant-sound task(Wöstmann et al., 2022). Studies on temporal regularity in distraction used distractors from a wide range of stimuli, spanning from pure tones (Bauer et al., 2015) to speech items

(Parmentier & Beaman, 2015). It is possible that the temporal regularity effect is more prominent with distractors that are more difficult to ignore. Thus, we started out with pure tone distractors in Experiments 1&2 and found that their temporal (ir)regularity did not affect working memory recall accuracy. We then employed spoken numbers as distractors in Experiments 3&4 to increase the degree of distraction.

Third, previous studies focused largely on primary performance metrics like the accuracy of memory recall, which reflects the precision of memory representation. However, it is conceivable that temporally regular versus irregular distractors rather affect secondary performance metrics of response behaviour during memory retrieval, which may involve metacognitive evaluation and threshold setting (Goldsmith & Koriat, 2007; Koriat & Goldsmith, 1996). Metacognition, usually operationalized as confidence rating, refers to one's evaluation and knowledge of the cognitive processes (Flavell, 1979). Metacognitive monitoring and control have been suggested to be involved in strategic regulation during memory recall (Koriat & Goldsmith, 1996). Specifically, response bias may represent a threshold in memory recognition: a participant would only respond that they remember the item (i.e., "old" item) if their confidence is higher than a certain threshold, which is related to faster response time (Atkinson et al., 1974; Banks & Atkinson, 1974; Juola et al., 1971). Therefore, studying how the temporal regularity of distractors influences response speed, confidence, and response bias would be required to obtain a comprehensive understanding of whether the temporal (ir)regularity of auditory distraction reaches awareness.

It is possible that, instead of interfering with the serial order memory as suggested by the changing state hypothesis, the temporal regularity of distractors may have a more general impact on the goal-directed response behaviour. In such case, instead of directly interfering with the serial memory recall accuracy, the temporal regularity of distractors may modulate the response behaviour (e.g., response speed and bias) which are less reflective of the serial memory maintenance but still sensitive to how distractors affect goal-directed behaviour (Kattner & Bryce, 2021; Makov & Zion Golumbic, 2020). Previous research found that temporal regularity of target stimuli increases confidence ratings, which was attributed to an increase in processing fluency, or the subjective experience of ease during information processing (Alter & Oppenheimer, 2009; Stevenson & Carlson, 2020). Furthermore, previous studies revealed a facilitatory effect of temporal regularity on response time in target detection tasks (Morillon et al., 2016; Rohenkohl et al., 2012; Salet et al., 2021), suggesting that the periodicity in regular stimuli may facilitate motor preparation. To explore whether temporal regularity of distractors also modulates processes other than the precision of items represented in memory, we included secondary performance metrics response time in Experiment 3, as well as response bias and confidence ratings in Experiment 4. In addition, we included visual distractors in Experiment 4 to investigate if the temporal regularity effect of distractors on working memory, if any, is modality-specific.

Across Experiment 1 to 4 in the current study, different variants of working memory tasks were used to investigate whether the temporal regularity of distractor affects working memory. Overall, we found no temporal regularity effect on the primary performance metric memory recall accuracy. However, temporal regularity was found to modulate participants' secondary performance metrics, reflected by response speed in Experiment 3, as well as response bias and confidence in Experiment 4.

4.2 Methods

4.2.1 Participants

Across all 4 experiments, N = 90 native German speakers (70 females, 20 males) aged 19 to 64 years (mean = 24.81, SD = 3.95) participated, among which N = 89 participants were included in the analyses. All participants provided written informed consent. Participation was compensated financially or by course credit. According to self-report, all participants were right-handed, had normal hearing, and had normal or corrected-to-normal vision. The experimental procedures were approved by the local ethics committee of the University of Lübeck and in accordance with the Declaration of Helsinki.

Due to technical issues, one participant in Experiment 1 finished only 184 out of 250 trials, the rhythmicity rating of one participant in Experiment 2 was not recorded, and the data of one participant in Experiment 3 were overwritten and thus missing. Two participants participated in more than two of our experiments that were at least 5 months apart from each other. Detailed information on participant samples for individual experiments can be found in Table 1.

4.2.2 Stimuli and procedure

Inspired by the well-established irrelevant-sound paradigm (Colle & Welsh, 1976), we used serial working memory tasks (Experiment 1-3) and a recognition memory task (Experiment 4) to present temporally regular versus irregular distractors during memory retention. For all experiments, each trial consisted of a memory encoding, retention, and retrieval phase. Prior to the execution of the main task, participants were instructed to maintain the order (Experiment 1 to 3) or the position (Experiment 4) of the target stimuli in mind while ignoring the distractor sequence presented during the retention period. The distractor onset delay, i.e., the onset of the distractor sequence after the offset of the target stimuli, varied across trials (see “Distractor onset delay” in Table 1). Here, we describe the general experimental design and important manipulations for each experiment (see Table 1 for all details).

In Experiment 1 (Figure 4.1A), a target sequence with numbers from 1 to 9 was presented visually in the center of the screen, in a random order, during the encoding period. The duration of each number presentation was 300ms, the stimulus onset asynchrony (SOA) between numbers was 600ms, and the total duration of the target stimuli was 5100ms. During the retention period, a distractor sequence was presented. The distractor sequence consisted of eight 1000-Hz pure tones with a 4-Hz presentation rate (i.e., SOA of 250ms). The SOA of the last distractor tone was manipulated across 5 levels: 125ms, 187.5ms, 250ms, 312.5ms, and 375ms. Regularity of the distractor sequence was given when the last distractor tone SOA was identical (i.e., 250ms; Regular) versus different (i.e., 125, 187.5, 312.5, and 375ms; Irregular) from the SOAs of the previous tones. After the retention period, participants recalled the target number sequence by typing it on the number pad of a keyboard. Afterwards, feedback was provided with green and red underscores under correct and incorrect answers, respectively.

In Experiment 2 (Figure 4.1B), the target was a pseudo-random permutation of German utterances of the digits 1 to 9, pronounced by a female speaker, with the constraint that no succeeding numbers (e.g., 3 and 4) be presented consecutively. The average duration of the numbers was 595ms and the SOA between numbers was 750ms (Wöstmann & Obleser, 2016). The distractor sequences consisted of eight 440-Hz pure tones (i.e., musical note A4) and were either temporally regular or irregular. For the regular sequence, the SOA was 250ms (4 Hz). For irregular sequence, the SOA was randomly selected between 100 and 400ms (10ms steps), with the constraint that the average SOA, as well as the last SOA, were each 250ms. In the retrieval period, participants navigated the screen with a mouse and selected the numbers from a number pad presented on the screen. No feedback was provided afterwards.

The target stimuli in Experiment 3 (Figure 4.1C) consisted of 8 numbers (numbers 1 to 8) also in a pseudo-randomized order as in Experiment 2, spoken either by a female or a male speaker. The numbers were shortened to 350ms using Praat (version 6.1.16; http://www.praat.org/). The perceptual centre of each stimulus was determined by first creating the 15-Hz lowpass-filtered envelope of the stimulus using Hilbert transform, and then finding the time point where the envelope reached 50% of the peak of the first syllable (Morton et al., 1976; Wöstmann et al., 2018). The interval between the perceptual centres of the numbers was 750ms. The temporal regularity of the distractor was manipulated in the same way as in Experiment 2, where spoken numbers of the distractor sequence were spoken by a female voice in case the target was spoken by a male voice and vice versa. For regular sequences, the SOA was 750ms (1.33 Hz). For irregular sequences, the SOA was randomly selected between 400 and 1100ms (10ms steps), with the constraint that the average SOA, as well as the last SOA, were each 750ms. Furthermore, a lower bound of temporal irregularity was implemented by the constraint that the standard deviation of SOAs within a trial was larger than 200ms. As in Experiment 2, participants navigated on the screen with a mouse to select the numbers on the number pad. No feedback was provided also in Experiment 3.

In Experiment 4 (Figure 4.1D), instead of having an acoustically presented number sequence, the target stimulus was a visually presented 3x3 matrix, including 8 numbers in 8 positions (the centre of the matrix was empty during encoding). The target stimulus was presented for 2000ms. The same parameters for the distractor stimuli as Experiment 3 were used in the auditory modality, except that the SOA for the irregular sequence was randomly selected using 16.7ms steps to account for the refresh rate (60 Hz) of the monitor, such that the irregular sequences were comparable between auditory and visual modalities. In the visual modality, the number sequences were presented in the centre of the screen consecutively with the same manipulation in terms of the temporal regularity of the distractors. After the retention period, a display with one probe number at one position was presented. Participants had to identify whether the probe number matched the target number in the encoding display at this position. The button assignment (i.e., left versus right) was counterbalanced for "match" versus "no match" responses across participants. Afterwards, participants indicated how confident they were that they answered correctly on a 4-point scale (1 = not confident at all, 4 = very confident). Participants also received no feedback in Experiment 4.

In addition to Experiments 1 to 4, a control experiment (N = 18, mean age = 23.68 years, SD = 2.83, 16 females, 2 males) was conducted to demonstrate the strength of interference by the tone and spoken number distractors, respectively, relative to when there was no distractor (i.e., quiet control condition). The target stimuli and response method were the same as in Experiment 3. The experiment was divided into four blocks with the lengths of the retention period fixed within each block. For half of the blocks, the retention period was 5s as in Experiment 2; for the other half, the retention period was 8s as in Experiment 3. In the 5s retention blocks, either no distractor (quiet control; 50% of all trials) or a tone sequence (distractor presence; 50% of all trials) used in Experiment 2 was presented during the retention period. The tone sequence was either temporally regular (50% of the distractor presence trials) or irregular (50% of the distractor presence trials) to maintain the same context as in the main experiment. Trials with different temporally regular and irregular distractors were combined in the analysis. The manipulations were the same in the 8s retention blocks, but with the spoken number sequences from Experiment 3 serving as distractors. There were 192 trials in total and 48 trials for each of the four conditions [distractor (present vs absent) x retention period (5s vs 8s)]. Block order was counterbalanced between participants, with half of the participants starting the experiment with the 5s retention period block and the other half with the 8s retention period block.

The relatively long retention periods (3 to 8s) in the current study were chosen to ensure a large enough dynamic range to manipulate the SOAs in the irregular condition. For example, in Experiment 3, given that the duration of speech stimuli was 350ms, we manipulated the temporal structure by constraining the SOAs to be within the 400-1100ms range with a mean of 750ms, the SOA employed in the temporally regular condition. As a result, the distractor sequence was relatively long (~5.6s) and a long retention period was employed. Differential distraction by speech of varying acoustic detail was also found in a previous study with a retention period longer than the one used in the current study (Wöstmann & Obleser, 2016). As the main research interest in the current study was to unravel the difference between temporally regular and irregular distractors, we compared the outcome measures between temporally regular and irregular conditions, holding the retention period constant between conditions within each experiment.

In all experiments, participants were instructed to keep their eyes open and not to speak the target numbers out loud. They were instructed to fixate the fixation cross in the middle of the screen during the encoding (for Experiment 2, 3, and 4) and retention (for Experiment 1 to 4) period whenever a fixation cross was presented.

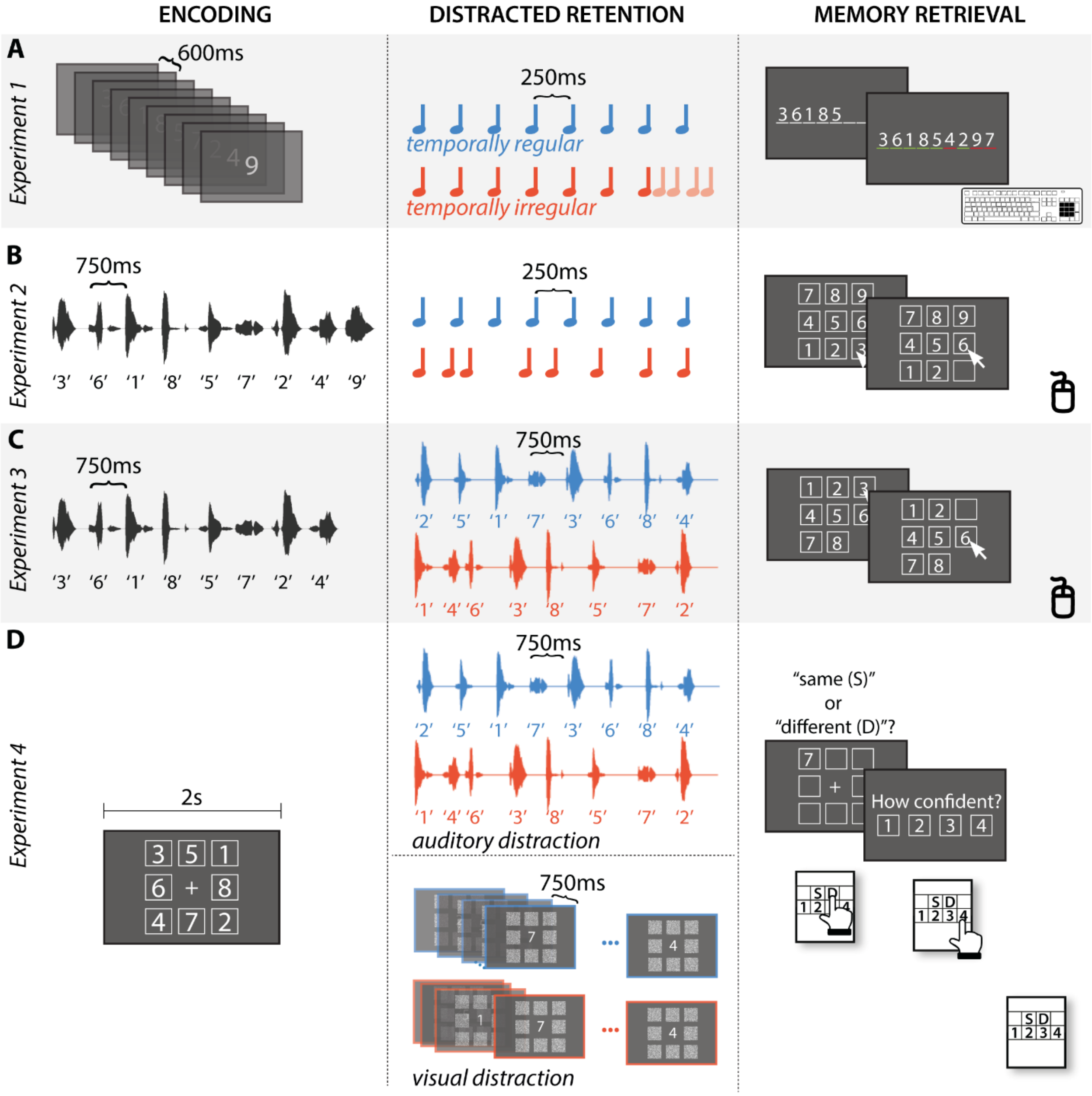

Figure 4.1. In all four experiments (A-D), participants maintained the target numbers in memory during the retention period while ignoring the distractors (blue/orange). In Experiment 1 (A), temporal regularity of distractors was manipulated by altering the onset of the last distractor tone such that it was either identical (regular, blue), or shorter/longer (irregular, red) than the stimulus onset asynchrony of the preceding distractor sequence. In Experiments 2 to 4 (B-D), the temporal regularity of the distractors was operationalized by the isochronous (regular, blue) or irregular (red) temporal structure of the entire sequence of distractors. After the retention period, participants responded with a mouse to select the numbers in their order of presentation from a visually presented number pad (Experiments 2 & 3), with a number pad on a keyboard (Experiment 1), or with a response pad (Experiment 4).

To check whether temporally regular distractors were perceived as more rhythmic than temporally irregular distractors, we also included a rhythmicity rating for distractor sequences after Experiments 2 & 3. Participants listened to all of the distractor sequences that were presented in the main experiment and rated how rhythmic they found each distractor sequence on a scale from 1 (not rhythmic at all) to 7 (very rhythmic) by clicking the number on the screen with a mouse. The distractor sequences were presented in a randomised order.

Experiments 1, 3, and 4 were implemented using MATLAB (MathWorks, Inc., Natick, USA) and Psychophysics Toolbox (Brainard, 1997). Experiment 2 was implemented as an online study, using Labvanced (Finger et al., 2017). Participants used headphones for Experiments 1, 3, and 4, while approximately half of the participants (N = 10) used headphones and the other half (N = 9) used speakers in Experiment 2 (according to self-report). The auditory materials were presented at comfortable listening levels. Details of all experiments are listed in Table 1.

4.2.3 Analysis

For Experiments 1 to 3, we analysed the effect of temporal regularity on working memory performance with repeated-measures ANOVAs or paired t-tests (2-tailed), using the data of individual experiments. To increase the power of the analysis, we also ran a mixed-design ANOVA for the combined data of Experiments 1–4 with temporal regularity as the within-subject factor and experiment as the between-subject factor. Accuracy was operationalised as the proportion correct of the serial recall, which, on the single-trial level, could take on 10 possible values (0-9/9) in Experiments 1 & 2, 9 possible values (0-8/8) in Experiment 3, and 2 binary values (0 = incorrect and 1 = correct) in Experiment 4. To delineate whether the empirical data speak to the alternative versus the null hypothesis, we complemented frequentist statistical analyses with the Bayes Factor (BF_{10}; Dienes, 2014; Jeffreys, 1939). As an effect size, we report $r_{\text{equivalent}}$, which is bound between 0 and 1 (Rosenthal & Rubin, 2003). $r_{\text{equivalent}}$ was derived from Cohen's d in the paired t-tests or eta-squared (η^2) from the repeated-measures ANOVAs using the transformation provided in an online tool (Lenhard & Lenhard, 2016) (https://www.psychometrica.de/effect_size.html).

For Experiment 1, we ran a paired t-test with the factor regularity, referring to the temporal delay between the last two distractor tones, which could either agree with the delays between all distractors earlier in the sequence (i.e., 250ms; denoted regular) or differed systematically (i.e., 125, 187.5, 312.5, or 375ms; denoted irregular). In addition, we ran repeated-measures ANOVAs to test the effect of the exact delay (in ms) between the last two distractor tones (denoted final distractor onset), as well as the absolute deviation of this delay from a regular distractor (i.e., |250ms – delay between last two distractor tones|; denoted final distractor deviation).

For Experiments 2 & 3, paired t-tests were used with the factor regularity, which referred to the temporal structure of the whole distractor sequence. We tested whether temporally regular distractors were perceived as more rhythmic than the temporally irregular distractors in Experiment 2 and 3, respectively, using paired t-tests with regularity as the factor. In Experiment 3, we recorded participants' response time in addition to accuracy. Response time (RT) was defined as the time interval between the presentation of the number pad on the screen and participants' first button press. We first converted response time into speed (1/RT), and then excluded 6% of the slowest (3%) and fastest (3%) trials (Ratcliff, 1993). We analysed the effect of temporal regularity on speed by replacing accuracy with speed in the analysis.

For Experiment 4, response time was defined as the time interval between the presentation of the response screen and the button press. We also converted response time into speed (1/RT) and excluded 6% of the slowest (3%) and fastest (3%) trials together with the trials without a response (approximately 3%). We implemented two analysis approaches. First, to examine whether there is an interaction between distractor modality and regularity, we employed repeated-measures ANOVAs on each outcome measure (i.e., accuracy, speed, and confidence) separately, with the factors modality and regularity. As the modality x regularity interaction was not significant, we collapsed across visual and auditory distractors for further analyses.

In addition, we ran trial-wise linear mixed models including trial number and distractor onset delay for all aforementioned analyses. As the patterns of the trial-wise analyses and the analyses on aggregated data converged, the results of the linear mixed models are not presented here.

Second, in Experiment 4, we used signal detection theory (Macmillan & Creelman, 2004) to derive sensitivity and response bias (criterion) separately for Regular and Irregular conditions, respectively, using Equations 4.1 and 4.2:

$$\text{Equation 4.1: Sensitivity} = z\ (\text{Hit rate}) - z\ (\text{False alarm rate})$$

$$\text{Equation 4.2: Criterion} = -0.5 * (z\ (\text{Hit rate}) + z\ (\text{False alarm rate}))$$

Hit rates and false alarm rates of 0 or 1 for individual participants were replaced by 1/2N, where N refers to the number of trials (Macmillan & Kaplan, 1985). Since sensitivity and response bias cannot be derived for single trials, we only used paired sample t-tests to test for the effects of distractor regularity.

As participants responded significantly more conservatively in the regular condition (i.e., more positive response bias) in Experiment 4, we further investigated the effect of regularity on the outcome measures. Higher response bias means that participants tend to respond "different" (i.e., "no" response), which suggests that participants may have different confidence ratings depending on whether the target and probe displays matched. Hence, we included the factor match, which classifies whether the target and probe displays were the same (match = 1; correct response = "same") or different (match = 0; correct response = "different"), into a 2-way repeated-measures ANOVA including the factor distractor regularity. We did not repeat these analyses on sensitivity and response bias as the factor match was taken into account while calculating the two measures (i.e., hit rate: response "same", match = 1). As in Experiments 1 to 3, we also included effect sizes and Bayes factors to quantify the strength of the evidence towards the alternative hypothesis. Bayes factors indicate the comparison between the likelihood of an alternative hypothesis to that of a null hypothesis (Jeffreys, 1939). For statistically significant results (i.e., $p < .05$), we used the Bayes factor not to decide whether there is an effect, but rather to estimate the strength of the evidence. More critically, for null results (i.e., $p > .05$), we used the Bayes factor to indicate whether the result is more likely to reflect the absence of evidence or evidence for the absence of an effect. Conventionally, Bayes factors (BF_{10}) > 3 indicate that the observed data are substantially more likely to speak to the alternative hypothesis than the null hypothesis, and vice versa with Bayes factors < 1/3. Bayes factors of 1 indicate that the data do not speak to either the alternative hypothesis or the null hypothesis.

Post-hoc power analyses with 20 and 89 participants were conducted, approximately matching the number of participants in individual experiments and the total number of participants, respectively. With N = 20, alpha = .05, and power = 0.80, the minimum effect size needed to reliably observe a significant effect (in a paired samples t-test) was $r = 0.31$. With N = 89, alpha = .05, and power = 0.80, the minimum effect size needed to reliably observe a significant effect was $r = 0.15$. The temporal regularity effects observed in the current study were smaller than these minimum effect sizes. We also compared the effect sizes observed in the current study to previous studies from the literature which found the effects of the temporal regularity of distractors on memory recall accuracy (D. M. Jones & Macken, 1995; Parmentier & Beaman, 2015). The effect sizes in the current study (e.g., $r = 0.009$ in the combined analysis) are considerably smaller than the effect sizes obtained in these studies, which were *r* = 0.42 (D. M. Jones & Macken, 1995) and *r* = 0.19 (Parmentier & Beaman, 2015), respectively. All statistical analyses were conducted in jamovi (version 1.6.23; www.jamovi.org).

Table 4.1. Details of experimental manipulations for each experiment.

		Experiment 1	Experiment 2	Experiment 3	Experiment 4
Participants	Sample size	n=21 (14f, 7m)	n=19 (18f, 1m)	n=20 (16f, 4m)	n=30 (22f, 8m)
	Age (years; M=mean; SD=standard deviation)	20-64 (M=26.95, SD=2.7)	19-38 (M=24.8, SD=5.74)	19-27 (M=22.7, SD=2.25)	19-32 (M=24.7, SD=3.54)
Encoding	Target duration	5.1s	~6.6s	~5.6s	2s
	# of targets	9	9	8	8
Retention	Retention duration	3s	5s	8s	8s
	Distractor onset delay	0.5-1s	1.035-1.835s	1.035-1.835s	1.035-1.835s
	Distractor type	pure tones (1000 Hz)	pure tones (440 Hz)	spoken numbers	spoken numbers/ numbers on screen
	Distractor duration	1.675-1.925s	1.8s	~5.6s	~5.6s
	Factors (# levels)	SOA (5)	Regularity (2)	Regularity (2)	Regularity (2) x Modality (2)
Retrieval	Response device	keyboard	mouse	mouse	response pad
	Outcome measure	Accuracy	Accuracy	Accuracy, Speed (1/RT)	Accuracy, Speed (1/RT), Criterion, Confidence
	Number of trials	250 (50 per condition)	108 (54 per condition)	120 (60 per condition)	256 (64 per condition)
	Number of blocks	5	2	2	4
	Inter-trial interval	1s	1s	1s	0.73 to 4s
	Block design?	No	No	No	Modality (visual/auditory)
Apparatus	Lab/online	Lab study	Online study	Lab study	Lab study
	Sound presentation	Headphone (Sennheiser HD 280 Pro)	Headphone (n = 10), speakers (n = 9)	Headphone (Sennheiser HD 280 Pro)	Headphone (Sennheiser HD 280 Pro)

Note. m indicates male. f indicates female. # indicates number. n indicates sample size.

4.3 Results

4.3.1 Temporal regularity of distractors does not affect working memory recall accuracy

We tested whether temporally regular versus irregular distractors would differentially affect working memory recall accuracy. Across Experiments 1–4, regular distractors did not interfere more with recall accuracy than irregular distractors ($F_{1,85} = 0.31$, $p = .577$, $r = 0.009$). The Bayes Factor for this contrast ($BF_{10} = 0.24$) provides evidence for the absence of an effect of temporally regular versus irregular distractors on the accurate recall from working memory. The interaction between distractor regularity and experiment was also not significant ($F_{1,85} = 0.51$, $p = .680$, $r = 0.020$, $BF_{10} = 0.10$), suggesting that the absence of the distractor regularity effect was consistent across all four experiments.

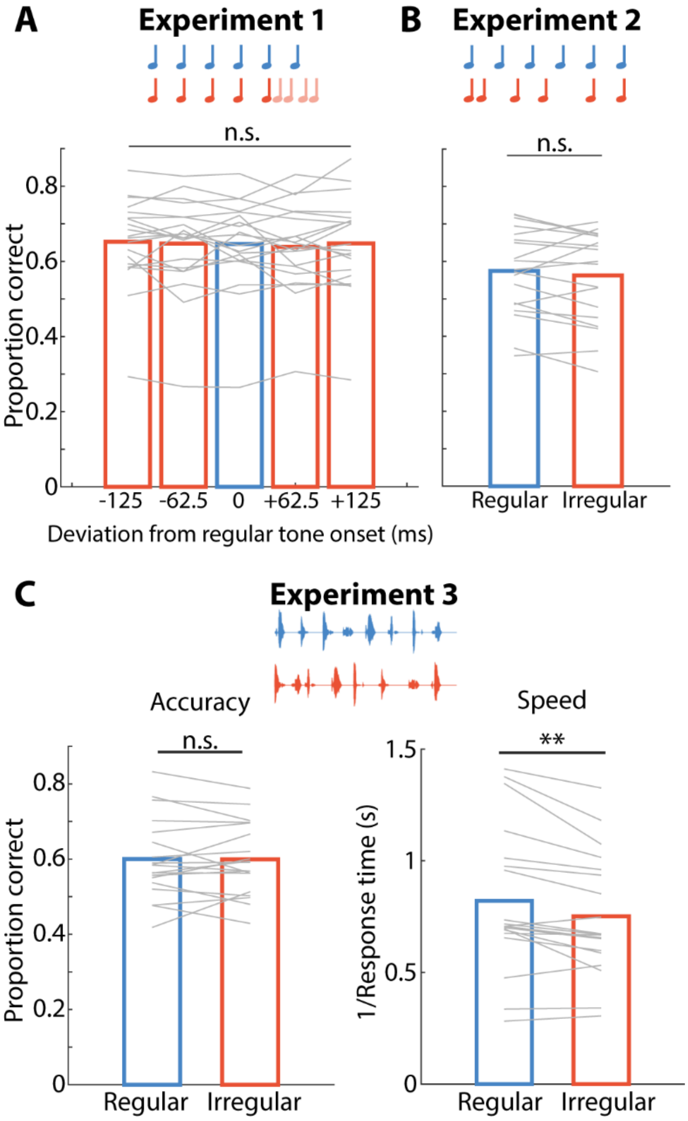

Figure 4.2. Serial recall performance in Experiment 1 (A), Experiment 2 (B), and Experiment 3 (C). A) Proportion correct for different deviations of the sequence-final distractor tone from temporal regularity in Experiment 1. B) Proportion correct in regular and irregular conditions in Experiment 2. C, left) Proportion correct in Experiment 3 for regular and irregular distractors. C, right) Response speed (1/RT). Bars show averages across all participants. Lines show data from individual participants. n.s. not significant. ** $p < .01$.

No significant effect of distractor regularity (regular versus irregular) was found in the analyses for individual experiments as well. For Experiment 1 (Figure 4.2A), whether the delay between the last two distractor tones was the same (regular) or different (irregular) from the 250-ms delays between previous tones in the sequence did not affect task accuracy ($t_{20} = -0.32$, $p = .975$, $r = 0.004$, $BF_{10} = 0.23$). Also, the exact delay of the final distractor tone (i.e., final distractor onset) and the absolute deviation of the final distractor tone from regular distractor (i.e., final distractor deviation) did not affect working memory recall accuracy (final distractor onset effect, $F_{4,80} = 0.51$, $p = .725$, $r = 0.039$, $BF_{10} = 0.09$; final distractor deviation effect, $F_{2,80} = 0.36$, $p = .701$, $r = 0.025$, $BF_{10} = 0.17$). In Experiment 2, regular distractor tone sequences were not more distracting than irregular sequences ($t_{18} = 1.12$, $p = .279$, $r = 0.127$, $BF_{10} = 0.41$; Figure 4.2B). Similarly, no effect on working memory recall accuracy was found for temporally regular versus irregular sequences of spoken numbers in Experiment 3 ($t_{18} = 0.07$, $p = .945$, $r = 0.008$, $BF_{10} = 0.24$; Figure 4.2C, left panel). Importantly, however, temporally regular distractors were perceived as more rhythmic than irregular distractors in both Experiment 2 ($t_{17} = 2.32$, $p = .033$, $r = 0.264$, $BF_{10} = 2.00$) and Experiment 3 ($t_{18} = 8.02$, $p < 10^{-5}$, $r = 0.677$, $BF_{10} > 10^{5}$).

To ensure that the lack of a temporal regularity effect cannot be attributed to a weak distraction effect in general, we additionally compared memory recall accuracy in the distractor-presence condition with a distractor-absence condition (i.e., quiet control condition) in a control experiment (Figure 4.3). The distractor presence x retention duration interaction was significant ($F_{1,17} = 29.10$, $p < .001$, $r = 0.114$, $BF_{10} = 13.36$), suggesting that the disruptive effect by different distractors varied. Post-hoc tests revealed that participants performed worse when tone distractors ($t_{17} = -3.30$, $p = .008$, $r = 0.336$, $BF_{10} = 6.68$) and when spoken number distractors ($t_{17} = -6.17$, $p < .001$, $r = 0.588$, $BF_{10} = 2174.82$) were presented, compared with the quiet control with the same retention period duration. Participants' memory recall accuracy did not differ for different retention period durations in the quiet control condition ($t_{17} = -0.10$, $p = .921$, $r = 0.012$, $BF_{10} = 0.24$). They performed worse with speech distractors in the 8s retention period block than with tone distractors in the 5s retention period block ($t_{17} = -4.68$, $p < .001$, $r = 0.483$, $BF_{10} = 142.80$). In sum, results of the control experiment demonstrated that the distractors used in the main experiments were indeed distracting.

Figure 4.4 shows the effects of distractor modality and regularity on different outcome measures in Experiment 4. For auditory compared with visual distractors, accuracy was lower ($F_{1,29} = 9.96$, $p = .004$, $r = 0.193$, $BF_{10} = 203.82$) and responses were faster ($F_{1,29} = 15.92$, $p < .001$, $r = 0.193$, $BF_{10} > 10^{5}$), but confidence did not differ significantly ($F_{1,29} = 2.45$, $p = .129$, $r = 0.115$, $BF_{10} = 2.66$). The main effect of regularity and the modality x regularity interaction were not significant for any of the measures (all $F < 1.5$, all $p > .25$).

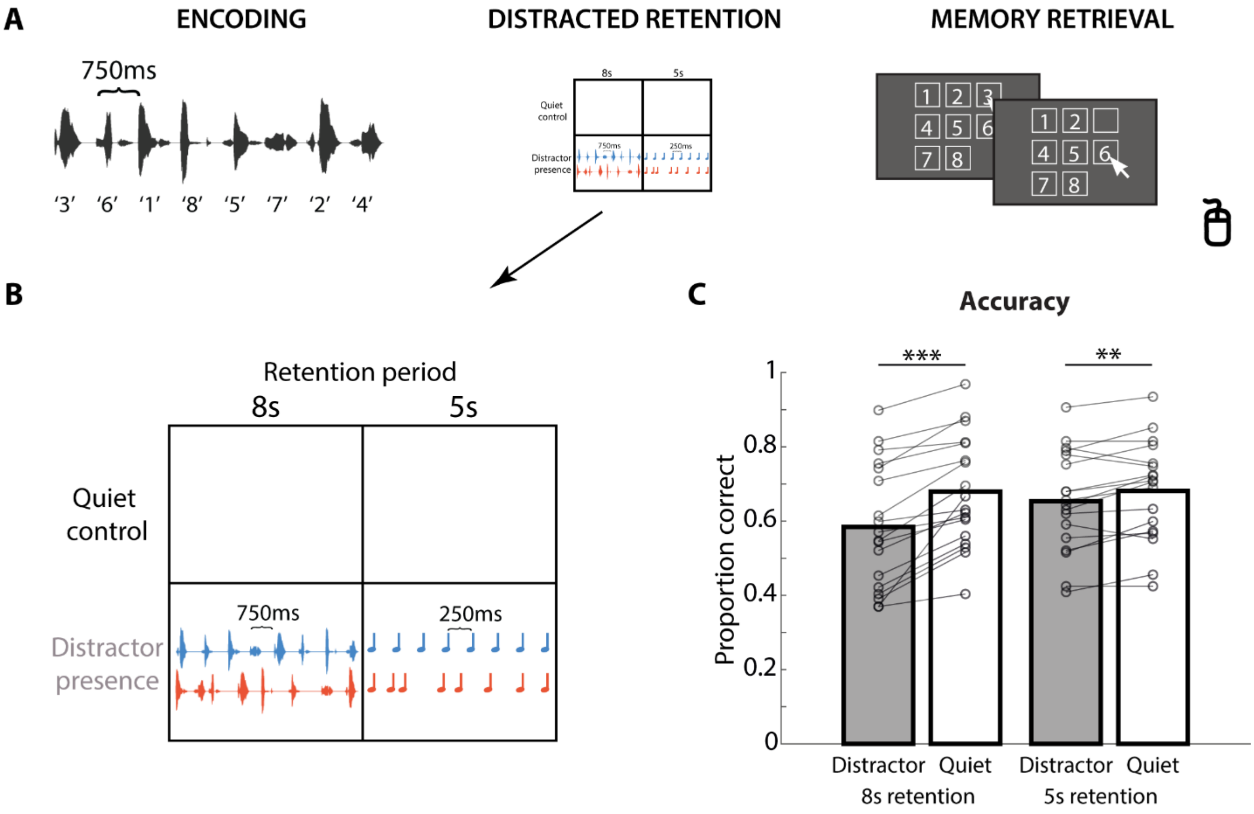

Figure 4.3. (A) Illustration of the trial structure in the control experiment, which was largely identical to the trial structure in Experiment 3. (B) Four conditions were implemented to cross the factors distractor (present vs absent) and duration of retention period (5s vs 8s). (C) Proportion correct scores in each condition in the control experiment. Lines show data from individual participants. ** p < .01. *** p < .001.

4.3.2 Temporal regularity of distractors affects response behaviour

We tested whether the temporal regularity of distractors influences secondary performance metrics in Experiments 3 & 4. As we additionally recorded response time in Experiment 3, we also investigated the effect of temporal regularity on the speed of the first manual response (i.e., first click on a number on the response screen). Participants responded significantly faster when the distractor sequence during retention was temporally regular (Fig. 2C, right panel; $t_{18} = 3.61$, $p = .002$, $r = 0.383$, $BF_{10} = 20.3$).

In Experiment 4, we also probed into the effect of distractor regularity using outcome measures derived from signal detection theory. Figure 4.5A and B show sensitivity and response bias (criterion), respectively, in regular and irregular conditions. We collapsed across modalities as no interaction between distractor modality and regularity was found in the previous analyses. Participants' sensitivity was not modulated by the temporal regularity of the distractor ($t_{29} = 0.62$, $p = .542$, $r = 0.056$, $BF_{10} = 0.23$). However, they responded more conservatively (i.e., higher tendency to respond "probe differs from encoding display") when the distractor was temporally regular versus irregular (t_{29} = 2.50, *p* = .019, *r* = 0.222, BF_{10} = 2.67).

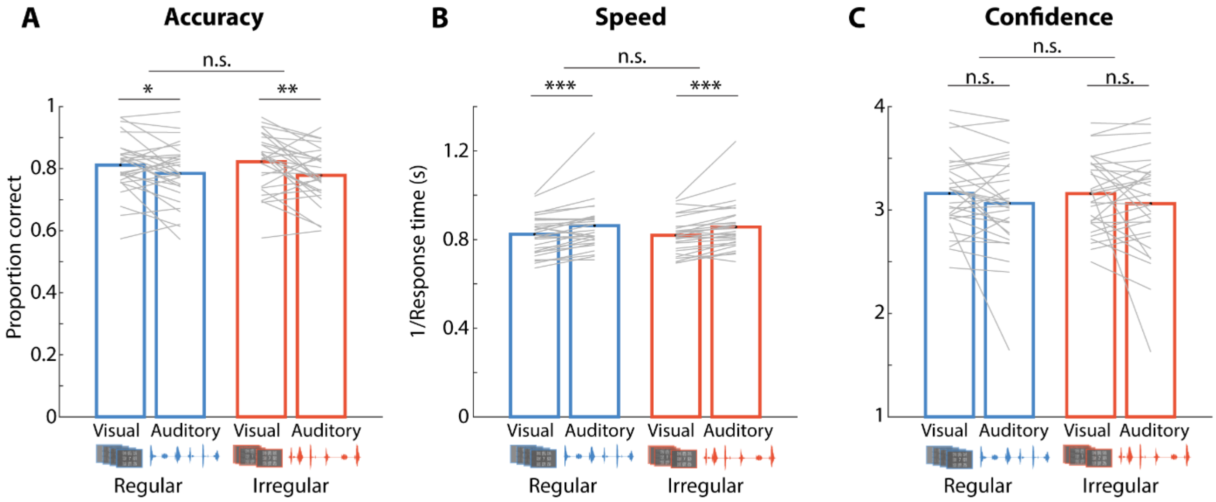

Figure 4.4. Bars show average accuracy (A), speed (B), and confidence rating (C) for distraction in different modalities (visual vs. auditory) and for regular vs. irregular distractors in Experiment 4. Lines show data from individual participants. n.s. not significant. * p < .05. ** p < .01. *** p < .001.

To follow-up on the effect of distractor regularity on response bias, we split up the metacognitive measure confidence in Experiment 4 for trials in which the memory probe matched versus mismatched with the encoding display. We thus used a repeated-measures ANOVA with the factors match and regularity, which revealed a significant match x regularity interaction on confidence with moderate evidence towards the alternative hypothesis ($F_{1,29}$ = 9.03, *p* = .005, *r* = 0.075, BF_{10} = 3.18). Figure 4.5C shows that participants were more confident in trials with regular distractors when the probe and target numbers did not match, and vice versa in the match condition.

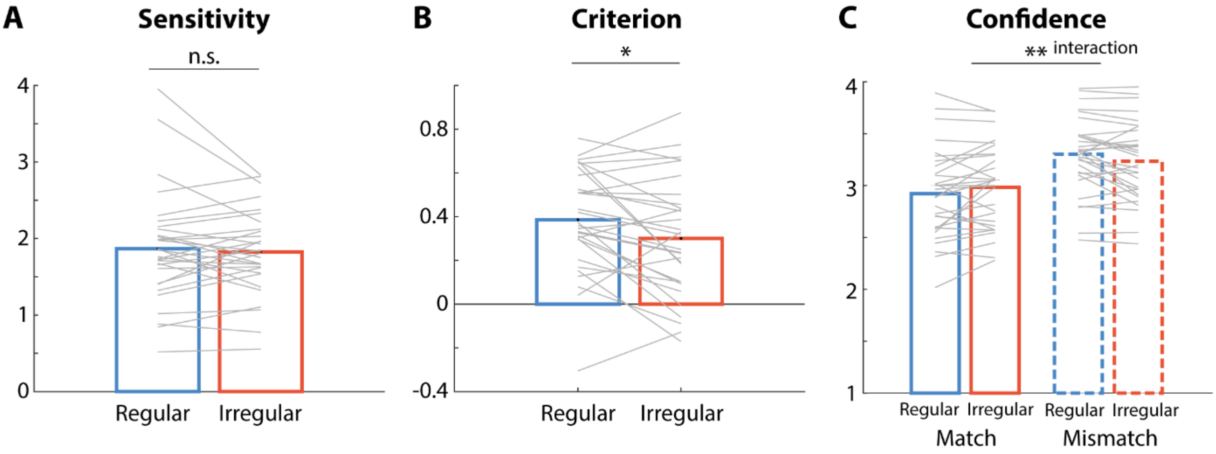

Figure 4.5. Sensitivity (A) and criterion (B) for temporally regular versus irregular distractors in Experiment 4. Bars shows means across all participants (N = 30). Lines show data from individual participants. (C) Interactive effect of temporal regularity and match, which refers to whether the memory probe matched with the encoding display, on confidence. n.s. not significant. * p < .05. ** p < .01.

4.4 Discussion

In the present study, we systematically manipulated different aspects of temporal regularity in distractor sequences and probed their impact on working memory. Distractor regularity did not modulate memory recall (Experiments 1-3) or recognition accuracy (Experiment 4), demonstrating that the absence of this effect is robust and generalises to different variations of working memory paradigms and operationalisations of temporal regularity. Nevertheless, regular versus irregular distractors had an influence on response behaviour, as reflected in response speed (Experiment 3), response bias, and confidence (Experiment 4). Our findings show that although temporal regularity of distractors does not inevitably affect primary performance metrics (recall accuracy), (ir)regularity of distractors does not go unnoticed and affects secondary performance metrics, which are often neglected in this field of research. A comprehensive understanding of auditory distraction requires that existing models of attention include secondary performance measures beyond recall accuracy.

4.4.1 No effect of temporal regularity of distractors on memory recall accuracy

The null results found in the current study may seem, at first glance, at odds with a previous study where the temporal regularity of distractors influenced target detection performance (Makov & Zion Golumbic, 2020). A crucial difference, however, is that all experiments in the present study separated the distractor in time from the target stream, which eliminated potential masking or interference effects during the encoding period. Thus, the present study tested the interfering effect of temporally regular versus irregular distractors on memory retention only, whereas higher interference for temporally regular distractors in the study by Makov & Zion Golumbic (2020) might reflect interference of target encoding.

Previous studies found inconsistent evidence for memory interference by temporally regular versus irregular distractors (D. M. Jones & Macken, 1995; Parmentier & Beaman, 2015). D. M. Jones & Macken (1995) suggested that a temporally irregular distractor sequence implements a changing-state sequence, which increases the disruption of working memory. In contrast, Parmentier & Beaman (2015) argued that irregular distractor sequences exhibit less distraction since distractors that are closer in time in an irregular stream might be grouped together, resulting in fewer transitions between units (Bridges & Jones, 1996). Both accounts approached temporal regularity of distractors as an attribute that influenced the degree of distraction by means of sequence segmentation. The current study could not support the speculations from either study as we found that regular versus irregular distractors did not affect memory retrieval at all, neither in the analyses on individual experiments nor the combined analysis. Of note, both studies mentioned had distractors presented throughout the entire encoding and maintenance period. It is thus possible that the temporal regularity of distractors has a bigger impact on memory encoding than on maintenance. Also, the current study only presented the distractor sequences in a portion of the retention period. In theory, it is possible that a longer sequence of distractors is needed to detect a temporal regularity effect of distractors on memory maintenance.

The current study revealed a null effect of temporal regularity of distractors on working memory recall accuracy by ensuring that the absence of an effect was not specific to certain experimental manipulations. Across the four experiments, we included visual or auditory targets, different distractor stimuli (e.g., pure tones or spoken numbers), as well as different manipulations of temporal regularity (e.g., violation or build-up of temporal regularity). We also complemented frequentist statistical analysis with Bayesian statistics to reveal whether non-significant results were more likely to arise from a true null effect (BF < 1) or were indifferent to null versus alternative hypotheses (BF = 1; Jeffreys, 1939). The Bayes factors smaller than .33 across different analyses (e.g., $BF_{10} = 0.24$ in the combined analysis of Experiments 1-4) suggest that temporal regularity of distractors during memory retention does not affect memory recall accuracy.

Here, we discuss three possible explanations for why the temporal regularity of distractors did not influence working memory performance. First, the influence of temporal regularity of distractors on memory retention may be frequency-specific. In attention research, rhythmic stimuli have been shown to modulate participants' performance maximally at 2 – 3 Hz (Farahbod et al., 2020), which falls into the range of the hypothesised resonance frequency of the attention network (Helfrich et al., 2019). It is possible that a resonance frequency also exists for the vulnerability to distraction. In a recent study, we found that the vulnerability to speech distractors fluctuates at around 2.5 Hz (Wöstmann et al., 2020). It might thus be that the frequencies of temporally regular distractors in the current study were either too slow (1.33 Hz in Experiment 3 and 4) or too fast (4 Hz for Experiment 1 and 2) to exert an influence on the eventual memory recall that would differ from temporally irregular distractors.

Second, it is possible that the irregular temporal structure we used in the current study, albeit being physically aperiodic, may be perceived as rhythmic by the participant. However, we do not consider it likely due to the results of the rhythmicity rating in Experiments 2 and 3.

In the current study, we defined temporal (ir)regularity in a strict manner by isochronous versus non-isochronous temporal structures. Stimuli with non-isochronous temporal structure, such as metrical musical rhythm or jittered SOA, may also be perceived as rhythmic and hence influence behaviour similarly to those with isochronous temporal structure (C. Keitel et al., 2017; Lakatos et al., 2008; Obleser et al., 2017). As we also included rhythmicity ratings in Experiments 2 & 3, we additionally compared the perceived rhythmicity between temporally regular and irregular distractors. Temporally regular distractors were indeed perceived as more rhythmic than irregular distractors. It is thus not likely that the absence of the effect arises from perceived rhythmicity of temporally irregular distractors in the current study.

Third, while previous studies demonstrated that neural or behavioural responses could be entrained by, i.e., temporally aligned to, temporally regular target stimuli (Obleser & Kayser, 2019), whether temporally regular distractors also exert similar influence remained unclear. The absence of effect in the current study agrees with the view that entrainment requires attention (Lakatos et al., 2013, 2019). In contrast with how we can better attend to the target stimuli presented at the expected time point, we are not more or less distracted by distractors presented at the expected time point compared with distractors presented at a random time point.

4.4.2 Secondary performance metrics are sensitive to temporal regularity of distractors

The results in Experiments 3 & 4 revealed that the temporal regularity of distractors posed an influence on participants' response behaviour. Temporal structures of stimuli, such as higher cueing frequency (Lin et al., 2021) or periodicity (Heynckes et al., 2020; Morillon et al., 2016), were found to have an impact on response speed. Consistently, in Experiment 3, participants responded faster after being exposed to regular distractors compared to irregular distractors. The facilitatory effect of temporal regularity on response speed might suggest that the readiness to respond may be modulated by the temporal regularity in distractors. A previous study using button presses as responses did not find a speed difference between rhythmic versus no distractors (Gorin et al., 2016). The current study differed from this study in terms of the operationalisation of temporal regularity (i.e., identical SOA versus repeating temporal structure), response type (i.e., by mouse versus by button presses), and control condition (i.e., irregular temporal structure versus quiet). In agreement with the present study, a recent study showed that temporal regularity of target stimuli led to motor preparation when a mouse was used as response device (Salet et al., 2021). Hence, it is possible that the periodicity embedded in regular distractors in Experiment 3 facilitates response speed through increased motor preparation.

No such speed difference between regular and irregular distractors was found in Experiment 4, which may be attributed to the difference in response type or task between the two experiments. Participants knew the first number to select from the response screen already during the retention period in Experiment 3, while they only knew the correct button press when the probe number was displayed on the response screen in Experiment 4. As a result, participants had ample time to prepare for the motor response in Experiment 3, but not in Experiment 4.

In Experiment 4, temporal regularity of distractors did not affect the accuracy of working memory but rather secondary performance metrics of participants. We found that response bias was more positive for regular distractors, indicating a stronger tendency to report a mismatch between encoding and probe displays and to respond “different”. Since this effect was unexpected, we can here only speculate about the underlying mechanisms. Response bias, and associated confidence ratings, were previously found to be subject to various factors such as the probability of a signal (Rhodes & Jacoby, 2007; Vickers & Leary, 1983). While we balanced the trial number of match and mismatch trials in Experiment 4, only 1 out of 8 numbers would match with the probe number in a match trial. This low probability of a match (i.e., signal) within a trial may contribute to the generally conservative behaviour of participants. With temporally regular distractors, participants may lean more towards their preferred response behaviour, which eventually results in more conservative (Experiment 4) and faster responses (Experiment 3). Furthermore, participants’ higher confidence when correctly responding “different” for trials with a regular versus irregular distractor is in line with this interpretation.

The distraction-effects on secondary performance metrics (speed & response bias) and metacognition (confidence) found in the current study speaks to the necessity to acknowledge these measures when the goal is to derive a comprehensive understanding of auditory distraction (Beaman et al., 2014). The role of distraction in the metacognitive evaluation of working memory performance has only been considered recently (Beaman et al., 2014; Kattner & Bryce, 2021). Beaman et al. (2014) found that distraction during encoding and retrieval interfered with the resolution of metacognitive monitoring when compared with quiet control. Kattner & Bryce (2021) showed that confidence diminished with a higher degree of distraction during encoding and retention. Our study demonstrated that distractors presented solely in the retention period also pose an influence on metacognitive evaluation and response behaviour, suggesting that the effect of distraction may be pervasive on cognition but also on metacognition.

4.5 Conclusion

The current study demonstrates that temporal regularity in the distractor stream during the retention period influenced response behaviour in working memory tasks. While distractor regularity in time did not affect the precision of the memory representation, it modulated the response behaviour and metacognitive evaluation of memory recall or recognition, reflected by response speed, bias, and confidence. The results of the current study set the stage for future research by showing the impact of temporal regularity in task-irrelevant stimuli on the often-neglected secondary performance metrics of goal-directed behaviour. Theoretically, the current study highlights the importance to yield a comprehensive understanding of how auditory distraction reaches awareness, and ultimately impacts task-relevant cognitive processes, by including these secondary performance metrics in existing models of attention.

5. Study 3: Does distractor predictability modulate behavioural and neural signatures of selective attention?

5.1. Introduction

The human brain constantly makes predictions of external events, even when they are outside of the centre of attention and distracting. Whether and how making predictions of these task-irrelevant distractors may facilitate or interfere with the ability to ignore them has only recently gained traction in the literature (e.g., Noonan et al., 2018; van Moorselaar & Slagter, 2020). Research on the influence of distractor predictability on its interference has mostly focused on global statistics on the distractor location (e.g., Failing et al., 2019; Wang et al., 2019). The current study aims at exploring the behavioural modulation and neural correlates related to distractor predictability derived from local statistics.

Predictable distractors are suggested to yield less disruptive influence on behavioural performance via expectation suppression (Noonan et al., 2018; van Moorselaar & Slagter, 2020). Expectation suppression is based on the prevalent predictive processing framework (Friston, 2005; Rao & Ballard, 1999) and is posited to take place irrespective of the task relevance of the stimulus (van Moorselaar & Slagter, 2020). According to the predictive processing framework (Friston, 2005; Rao & Ballard, 1999), the human brain forms a prediction of the incoming stimulus based on the statistical regularities embedded in the stimulus history. An error signal, i.e., a prediction error, would be generated when the incoming stimulus does not match with the expected stimulus and an update of the prediction model is warranted. The reduction in information to be processed in predictable distractors leads to a higher expectation and renders the predictable distractors easier to be ignored.

While distractor suppression by expectation receives much empirical support in recent years, the empirical evidence mostly came from spatial attention studies manipulating the global probability (i.e., item frequency) of distractor location (Failing et al., 2019; Wang et al., 2019; see van Moorselaar et al., 2020 where feature-based expectation was included) in the visual modality. While these studies contributed greatly to the understanding of distractor expectation, they do not suffice to provide a comprehensive view for the following reasons: First, using global probability to manipulate distractor expectation inevitably introduces a confound called intertrial priming, which refers to the influence of the preceding trial when a stimulus is repeatedly presented (Maljkovic & Nakayama, 1994, 1996). While some studies could still find behavioural modulation by distractor expectation after accounting for intertrial priming (e.g., Failing, Feldmann-Wüstefeld, et al., 2019; Golan & Lamy, 2022; Goschy et al., 2014; but see van Moorselaar et al., 2021), the intertrial priming effect is not negligible and should be avoided by experimental design (e.g., Bogaerts et al., 2022).

Second, apart from global statistics such as item frequency, the human brain was shown to also employ local statistics in predicting future events (Koelsch et al., 2016; Mittag et al., 2016). Specifically, the human brain is capable of detecting transition probability, which refers to the probability of each possible transition between/within items (Meyniel et al., 2016). A higher global probability does not only reflect a higher absolute item frequency; it also entails a higher probability of item repetition within a sequence. The expectation suppression account posits a reiterative process that takes place according to the statistical regularity at the local scale (Chelazzi et al., 2019; Noonan et al., 2018). Showing the formation of distractor expectation with local transition probability free from the influence of global statistics provides direct evidence supporting expectation suppression.

Third, spatial and feature-based distractor expectation may not have the same influence on distractor interference. Although both types of expectation were shown to employ frontoparietal regions, some cortical regions showed more activity in spatial attention versus feature-based attention (Giesbrecht et al., 2003). The spatiotemporal pattern of parietal activity was also found to differ for spatial and feature-based attention (Greenberg et al., 2010). Van Moorselaar et al. (2020) found an interaction between spatial distractor expectation and feature-based distractor expectation on reaction time. Feature-based expectation may thus not influence the behavioural and neural responses in the same way as spatial expectation. Given that most of the studies thus far investigated the influence of spatial expectation on distractor interference, more evidence on feature-based expectation is needed to yield a more comprehensive understanding of distractor expectation.

A scrutiny of the relatively thin body of literature on distractor predictability at the local scale reveals a less straightforward picture than the evidence in global probability. While one previous study showed better change detection performance when the distractor contained a repeating and thus regular tone sequence (Southwell et al., 2017), others studies on semantic predictability of speech distractor (Wöstmann & Obleser, 2016) or trial-by-trial predictability of distractor presence (Bogaerts et al., 2022) did not. In a previous study (Ma & Abrams, 2022), participants were able to suppress salient distractors even when they were unpredictable. The inconsistency in the literature is surprising given that numerous studies demonstrated that the brain is capable of extracting local statistical regularities, such as the transition probability, in a sequence outside the focus of attention (Dürschmid et al., 2018; Koelsch et al., 2016; Mittag et al., 2016). The inconsistent evidence begs the question of whether distractor predictability's influence on the final degree of distraction hinges on other factors related to distractor interference.

The load theory of attention may provide a cursor regarding the possible directions in which distractor predictability influences the ultimate distraction (Lavie, 1995; Lavie & Tsal, 1994; G. Murphy et al., 2016). The load theory of attention proposed that when the perceptual load in the environment is sufficiently high, the task-irrelevant distractors are not processed, reducing their potency to distract. On the other hand, cognitive control is an essential factor influencing the degree of distraction when the perceptual load is low. In such a case, increasing cognitive load (e.g., increasing working memory load) would essentially reduce the cognitive control capacity, thereby increasing the degree of distraction. There has been a rich body of literature on the visual modality supporting the load theory of attention (e.g., de Fockert et al., 2001; Gutteling et al., 2022; Lavie & De Fockert, 2003), demonstrating the ultimate detriments posed by distractors depend on the perceptual or cognitive load of a task. In the auditory modality, however, whether distractor interference depends on the perceptual load of the task remains unclear (S. Murphy et al., 2017).

How may distractor expectation interact with perceptual or cognitive load? There has been, to our knowledge, no direct evidence regarding the interaction between load and distractor expectation. In Töllner et al. (2015), the predictability of target-distractor similarity modulated performance only when the target and the distractor were dissimilar, which could be interpreted as evidence in favour of the hypothesis that lower perceptual load leads to higher distractor interference when target and distractor are predictable. For cognitive load, working memory recall accuracy of digits in a primary task was found to differ with different levels of semantic predictability in the secondary task, showing that stimulus predictability in one task may influence the performance of another concurrent task (Hunter & Pisoni, 2018). Under the framework of the load theory, we hypothesise that distractor predictability had a larger influence on the ability to ignore distractors with a lower perceptual load or with a higher cognitive load.

Given the scarcity of behavioural evidence of the local predictability of distractors, the neural evidence showing distractor processing with varying local predictability is as limited. Only a handful of electrophysiological studies examined the neural mechanism underpinning distractor expectation in the visual modality (e.g., Noonan et al., 2016; van Moorselaar et al., 2020, 2021; Wang et al., 2019). Those studies only manipulated expectation by global statistics and were mostly interested in two forms of neural measures: Alpha lateralisation, a well-established neural index of attentional selection (Haegens et al., 2011; Kerlin et al., 2010; Worden et al., 2000), and event-related potential (ERP) components. Among those studies, only one discovered an effect of location probability on pre-stimulus alpha lateralisation (B. Wang et al., 2019). N2pc and distractor positivity (P_D) components, which are the two typical candidates when studying visual spatial attention, were also associated with the global probability of both targets and distractors (van Moorselaar et al., 2020; B. Wang et al., 2019) or only with the global probability of distractors (e.g., late P_D in van Moorselaar et al., 2021).

While the expectation suppression account posits that there exists a preparatory neural mechanism in relation to ultimate distraction, the timing in which distractor expectation exerts an influence on distractor processing is still a subject of debate (van Moorselaar & Slagter, 2020). Specifically, it is unclear whether distractor expectation already influenced pre-stimulus neural measures of distraction or is only evident at the post-stimulus stage. Instead of a modulatory influence on pre-stimulus alpha lateralisation, van Moorselaar & Slagter (2020) showed that the brain may form a distractor template before distractor onset when the distractor was predictable using multivariate pattern analysis. Expectation built by distractor predictability may thus be reflected in other pre-stimulus neural measures other than alpha lateralisation. Second, although alpha lateralisation was generally regarded as a neural response reflecting preparatory selection, recent studies have shown post-stimulus alpha lateralisation in selective attention (Bacigalupo & Luck, 2019; Klatt et al., 2018a; van Diepen et al., 2016) or working memory (Klatt et al., 2018b) paradigms. It is also conceivable that alpha lateralisation serves as a neural correlate of reactive attentional filtering which is modulated by distractor predictability.

There is a longstanding line of research elucidating the ERP correlates of predictive processing (e.g., Abbasi et al., 2022; Schoknecht et al., 2022; Sussman et al., 1998) or attentional selection (e.g., Wöstmann et al., 2015). Before the stimulus onset, contingent negative variation (CNV), a slow wave component traditionally associated with timing (Kononowicz & Penney, 2016; Walter et al., 1964), may also reflect other cognitive operations such as attentional selection (Wöstmann et al., 2015), working memory (Wiener & Thompson, 2015), and expectation (Chennu et al., 2013). Post-stimulus sustained responses have been associated with working memory (Schneider et al., 2020), the proneness to distraction (Chao &

Knight, 1998; Vogel et al., 2005), and the predictive process (Coderre et al., 2020; León-Cabrera et al., 2019). Furthermore, modulations of the early ERPs such as N1 have also been observed in previous studies examining factors such as perceptual load (Sabri et al., 2013) and working memory load (Sabri et al., 2014). Distractor predictability may potentially have an interactive influence with the perceptual or cognitive load on the cascade of ERP responses underlying different cognitive operations.

The aim of the current study was twofold: First, we aimed to demonstrate the formation of distractor expectation by local transition probability. Second, we probed into the neural mechanism of distractor expectation with the focus on two main neural measures: Alpha lateralisation and ERP components. Of note, this chapter presents the preliminary data of N = 15. The statistical analyses and the conclusion derived from the results should only be considered with caution due to insufficient power.

To this end, participants performed a selective attention task where they had to attend to one side of the auditory input and ignore the other side. On the attended stream with different perceptual loads, participants performed a working memory task while ignoring the other stream, which could either be predictable or unpredictable. Behaviourally, we found that participants' behavioural sensitivity was modulated by the interaction of perceptual load, working memory load, and distractor predictability. Neurally, we found that post-stimulus alpha lateralisation differed between predictable and unpredictable distractors. We also found that CNV and sustained frontal negativity were modulated by the interaction between working memory load and distractor predictability. These results collectively demonstrate that the human brain not only forms expectations solely based on the local statistical regularity of the to-be-ignored distractors; but is also subject to distractor expectation in its influence on the ultimate degree of distraction.

5.2. Methods

5.2.1. Participants

Fifteen university students (10 females 5 males, mean age = 25.4, SD = 3.58), who were either native German speakers or non-native German speakers with high German proficiency, participated in the EEG experiment for either course credits or €10/hour with written informed consent. According to self-report, they were right-handed (mean Edinburg Handedness

Inventory score = 86.1; Oldfield, 1970), had normal hearing, and had no neurological or psychological disorders. All experimental procedures were approved by the local ethics committee of the University of Lübeck.

5.2.2. Stimuli and Procedure

Participants performed a version of the n-back task (Figure 5.1A) with the manipulation of working memory load (1 versus 2 back), signal-to-noise ratio (SNR; 0 dB versus -10 dB), and distractor predictability (predictable versus unpredictable). The auditory stimuli used in the current study were German numbers from 1 to 8, spoken by a female talker, and were shortened to 350 ms using the Praat software (version 6.1.16).

Before each block (Figure 5.1A), a cue was presented in the centre of the screen to indicate the to-be-attended side (left or right) and the working memory load (1-back or 2-back) of that block. Participants were instructed to attend to the cued side (target stream) and ignore the other side (distractor stream). For each trial, the target and the distractor numbers were presented simultaneously. Onset-to-onset interval between 2 numbers of a stream was 2s.

The working memory load was manipulated by the number of targets participants had to maintain in memory. In the target stream, a number sequence consisting of the target numbers was presented in a randomised manner. Participants had to press the response button whenever the current target matched with the target 1 or 2 numbers prior to the current number. For example, in the 1-back block, participants had to press a button whenever a number was presented 2 times in a row (e.g., **2**-**2**). In the 2-back block, participants had to press a button when the current number at trial n was the same as the number before the previous number at trial n – 2 (e.g., **2**-3-**2**). In each block, 20% of the trials (i.e., 24 trials) contained a match where participants should press a button.

The perceptual load was manipulated by the SNR between target and distractor streams (Figure 5.1B, left), which was analogous to the noise manipulation in a visual study of perceptual load (Gutteling et al., 2022). Specifically, the target stream was either presented at the same intensity as the distractor stream at 70 dB SPL or 10 dB SPL softer than the distractor stream. This means that the targets were presented at 70 dB SPL in half of the blocks (i.e., SNR at 0 dB) or 60 dB SPL in another half (i.e., SNR at -10 dB). Participants were not informed of the SNR before each block. Instead, they were told prior to the main experiment that the loudness in the main experiment may vary from block to block.

Distractor predictability was operationalised as the transition probability of the distractor numbers in each block (Figure 5.1B, right). In the predictable block, a randomly generated 4-number pattern was presented repeatedly over the block, resulting in a transition probability of 1. In the unpredictable block, the same 4 numbers were presented in a pseudo-random order, with the constraints that each number at trial n was different from the previous number at trial n – 1 and the number before at trial n – 2. The constraints were implemented to avoid unwanted potential confounds such as repetition suppression (Grill-Spector et al., 2006) or negative priming (Maljkovic & Nakayama, 1994). This resulted in a transition probability of 0.5 for each distractor number after the first two numbers in a block.

There were 16 blocks in total, with each unique block (e.g., SNR 0 dB, 1-back, predictable distractors) repeating twice in the experiment. For each participant, the numbers 1 to 8 were randomly sorted into two groups. In half of the blocks, one group of numbers served as targets while the other group served as distractors, and vice versa in the other half of the blocks with the same conditions. Similarly, participants attended to the left side in half of the blocks and to the right side in the other half of the blocks with the same conditions. There were 120 target/distractor pairs per block and 1920 target/distractor pairs for the whole experiment. The auditory materials were presented via the Sennheiser headphone (HD 25-1 II). A response box (The Black Box Toolkit) was used to collect behavioural responses. Stimuli were presented with Psychtoolbox (Brainard, 1997) and Matlab (MathWorks, Inc., Natick, USA).

5.2.3. Behavioural analysis

To study how distractor predictability modulates behavioural performance under different conditions, we calculated the outcome measures under signal detection theory (Macmillan & Kaplan, 1985), sensitivity (d'), and criterion (i.e., bias; c), with Palamedes toolbox (Prins & Kingdom, 2018) for each condition of SNR, working memory load, and distractor predictability. The first one (for 1-back block) or two (for 2-back block) trials of each block were excluded in the behavioural analysis as there would be no previous number to be compared to. A hit was defined as a button press when the target number at trial n matched with the previous number at trial n – 1 (for 1-back condition) or the number at trial n – 2 (for 2-back condition). A false alarm was defined as a button press when the target number in trial n did not match with the number at a previous trial (n – 1 for 1-back and n – 2 for 2-back condition). Sensitivity was calculated by subtracting the z-transformed false alarm rate from the z-transformed hit rate. The criterion was calculated by adding the z-transformed hit and false alarm rate and then multiplying the number by -0.5.

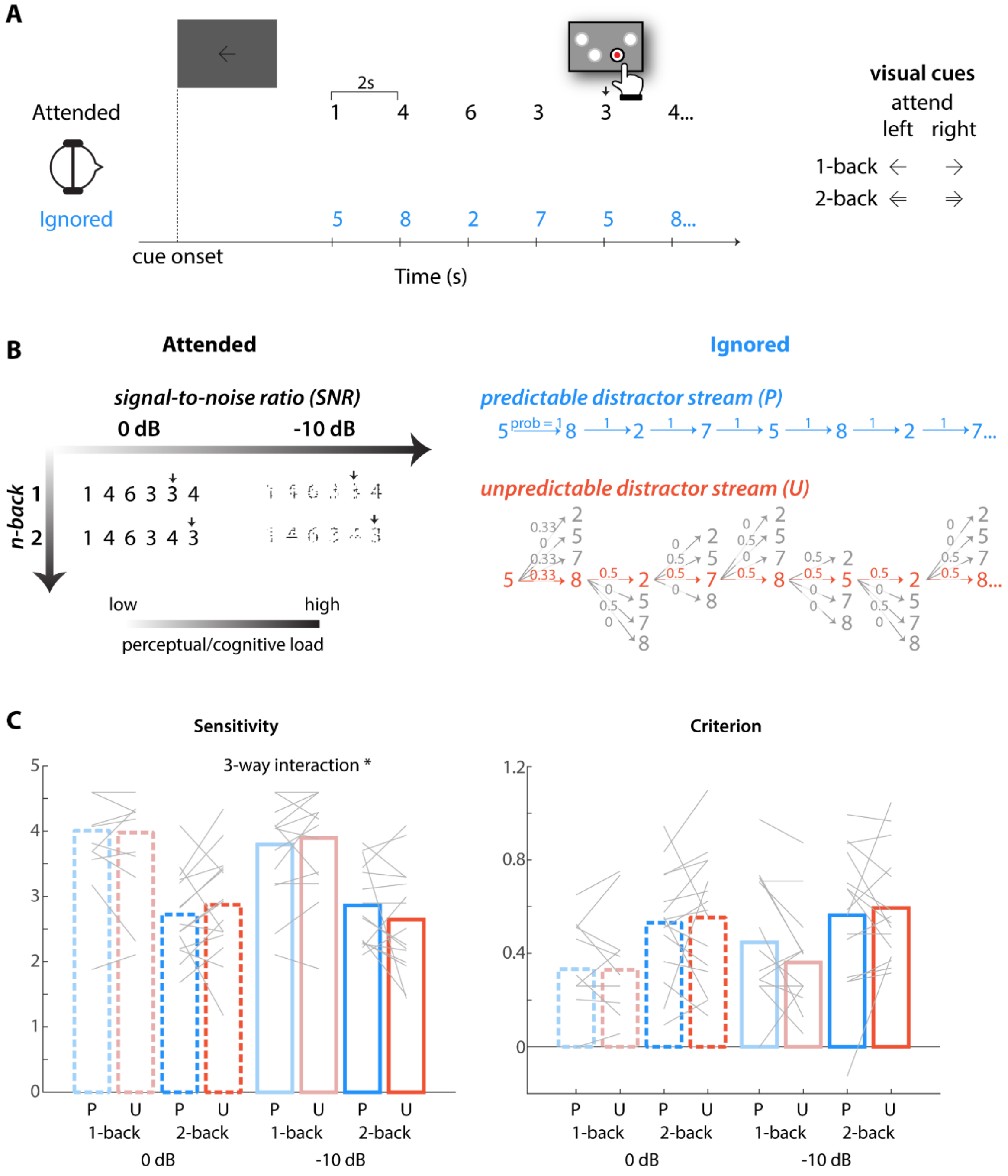

Figure 5.1. Experimental design (A-B) and behavioural results (C). A, left) A schematic of a block (attend-left, 1-back) during the experiment. Participants attended to one side (attended) while ignoring the other side (ignored). The cue display stayed on the screen during the whole block in the experiment. Participants had to press the red button whenever the current number matched with a previous number. A, right) The visual cues used in the experiment. Participants were informed of the attended side and the working memory task before each block. B, left) Manipulations on the attended stream. Perceptual load and cognitive load were manipulated by changing the stimulus intensity in the attended stream (signal-to-noise ratio) and the number of stimuli held in working memory (n-back), respectively. B, right) Manipulation of distractor predictability in the ignored stream. Predictability was operationalised as the transition probability between the distractors. C) Behavioural sensitivity (left) and criterion (right) by the factors SNR, working memory load, and distractor predictability. Bars show the averaged behavioural performance. Grey lines show data from individual participants. * $p < .05$.

Equation 5.1: Sensitivity (d') = z (Hit) – z (False alarm)

Equation 5.2: Criterion (c) = -0.5 * (z (Hit) + z (False alarm))

A hit or false alarm rate of extremes values (0 or 1) was adjusted with the corrected value, which was computed by dividing 1 by 2 times the number of trials (Macmillan & Kaplan, 1985). A value of 0 was replaced by the corrected value, while a rate of 1 was adjusted by subtracting the corrected value from 1. Since sensitivity and criterion can only be derived using aggregated data, we employed two repeated measures ANOVAs with factors SNR, working memory load, and distractor predictability on the two behavioural measures separately.

5.2.4. EEG recording and pre-processing

The experiment was done in a sound-attenuated and electrically shielded room. EEG data were recorded using the 10-10 international system with 64 Ag/Ag-Cl electrodes (actiCHamp, Brain Products, München, Germany) with an online bandpass filter from direct current (DC) to 280 Hz. The sampling rate was 1000 Hz. TP9 (left mastoid) and FPz were the online reference and ground electrodes, respectively. For all participants, the impedances of the electrodes were kept below 20 kOhm.

The EEG data were pre-processed using Matlab R2018a (MathWorks, Inc., Natick, USA) and the Fieldtrip toolbox (Oostenveld et al., 2011) with the following procedure: First, the continuous data were filtered (high-pass filter: 0.1 Hz; low-pass filter: 100 Hz) and then segmented into epochs of 2 s (-1 to 1s) time-locked to the target/distractor pair onset. Then, artefacts such as eye blink and muscle activity were identified and rejected by using independent component analysis (ICA). On average across participants, 32.17% of the components were rejected (SD = 6.67%). A bad channel (i.e., CP1) on one participant was interpolated after rejecting the ICA components. EEG epochs were re-referenced to the average of all electrodes. Afterwards, trials containing absolute EEG amplitudes exceeding 160 μV were excluded. The first one (for 1-back block) or two (for 2-back block) trials of each block, which were excluded in the behavioural analysis, were also excluded in the EEG analysis.

5.2.5. Analysis of alpha lateralisation

Single-trial EEG data were decomposed into time-frequency representations via a fast Fourier transform (FFT) with a moving time window of 500 ms (Hanning taper). Complex Fourier coefficients were obtained from -1 to 1 s (steps of 0.05 s) relative to target and distractor onset, and in a frequency range from 1 to 50 Hz in steps of 1 Hz.

Attentional modulation index (AMI) was calculated per time point and frequency on the absolute power to quantify the degree of attentional selection. First, trials belonging to the attend-left condition or the attend-right condition, respectively, were averaged. Then, AMI was obtained by the difference in the power spectra between the attend-left and attend-right conditions divided by the sum of the two:

$$\text{AMI} = (\text{Power}_{\text{attend-left}} - \text{Power}_{\text{attend-right}}) / (\text{Power}_{\text{attend-left}} + \text{Power}_{\text{attend-right}})$$

A positive AMI means that the alpha power when participants attended left was higher than when participants attended right. As attentional selection is said to be reflected by a contralateral decrease in alpha power and an ipsilateral increase in alpha power to the attended side (Worden et al., 2000), we would expect a higher AMI at the electrodes in the left hemisphere compared to those in the right hemisphere.

To test for alpha lateralisation, we averaged the AMI across frequencies within the alpha frequency band (i.e., 8 – 12 Hz) and across a selection of posterior electrodes belonging to the left and right hemispheres, respectively. The electrodes of interest were the same as in a previous study using the same EEG acquisition system (Wöstmann et al., 2019), which included TP9/10, TP7/8, CP5/6, CP3/4, CP1/2, P7/8, P5/6, P3/4, P1/2, PO7/8, PO3/4, and O1/2. A cluster permutation test (two-tailed) was conducted to find the time window in which the AMI in the left electrodes was larger than that in the right electrodes. The AMI difference between left and right electrodes was close to significant following the onset of target and distractor (i.e., 0.25 to 0.55 s).

To examine the influence of distractor predictability on alpha lateralisation, we further calculated the alpha lateralisation index (ALI) using the same set of electrodes as the previous analysis. For trials with predictable distractors, trials belonging to attend-left and attend-right conditions were averaged separately. Then, for each of the average power spectra, the alpha power (i.e., 8 – 12 Hz) in the electrodes on the contralateral side was subtracted from that on the ipsilateral side, and then divided by the sum of the two.

$$\text{ALI} = (\alpha_{\text{ipsi}} - \alpha_{\text{contra}}) / (\alpha_{\text{ipsi}} + \alpha_{\text{contra}})$$

The ALIs for the attend-left and the attend-right conditions were then averaged. ALIs for unpredictable distractors were calculated in the same way.

The ALIs between 0.25 to 0.55s, the time window where the previous cluster-based permutation test was close to significance, were averaged for further statistical testing. One-sample t-tests against zero were conducted for the ALI in predictable and unpredictable conditions, respectively. A paired-sample t-test (two-tailed) comparing predictable and unpredictable distractors was conducted to test whether there was a difference in ALI between the predictable and the unpredictable conditions.

5.2.6. ERP analysis

The EEG epochs were first baseline corrected (-0.2 to 0 s) and re-referenced to the average of mastoid electrodes (i.e., TP9 and TP10). Then, the EEG epochs belonging to each condition (SNR X working memory load X distractor predictability) were averaged to compute the event-related potential (ERP) waveform.

The ERP components N1, P2, sustained frontal negativity (SFN), and contingent negative variation (CNV) were studied in the current study. For N1 and P2 components, the time window was determined by the mean amplitude around the peak of the grand average ERP waveform across all conditions and all participants. The N1 amplitude was extracted at 75ms to 125ms post-stimulus onset, which was 50ms around the peak amplitude at 100ms. For the P2 amplitude, the positive peak in the grand average ERP waveform was at 180ms and the time window used to extract P2 amplitude was from 155 to 205ms. As the effect of the sustained frontal negativity was robust and stable across time, the ERP data between 400 to 900ms were averaged to obtain the sustained frontal negativity.

Instead of amplitude, the slope of the ERP waveform in the pre-stimulus time window (-800 to 0ms) was used as the measure of CNV by fitting a linear trend on the ERP waveform of each condition using the “polyfit” function on Matlab (order = 1). CNV slope instead of amplitude was used to avoid the spurious effect resulting from the choice of baseline. A baseline between -200 and 0ms was chosen in the current study to examine the post-stimulus ERP components. However, the time window right before stimulus onset would coincide with the time window at which CNV amplitude would be the most prominent. A previous studies also used the linear trend of pre-stimulus neural activity to measure the strength of CNV (Chennu et al., 2013). Hence, we decided to calculate the linear trend of the pre-stimulus EEG activity with a rather long time window (i.e., 800ms) to capture the progression of pre-stimulus neural activity.

The electrode with the maximum amplitude (slope for CNV) for each ERP component, as well as the two adjacent electrodes at the left- and the right-hand side, were used to calculate the ERP amplitude. As a result, The N1 amplitude was calculated using electrodes C1, Cz, and C2. The P2 amplitude was calculated using electrodes FC1, FCz, and FC2. The sustained frontal negativity was calculated using electrodes F1, Fz, and F2. Lastly, CNV was calculated using electrodes PO3, POz, and PO4.

We examined the effect of SNR, working memory load, and distractor predictability on each ERP component using single-trial linear mixed-effects models. For each trial, we averaged the amplitudes of the EEG data at the time windows and electrodes of interest. Then, we regressed the ERP component on the main effects and interaction effects of the predictors and participant as a random intercept. All variables in the model were z-score transformed.

In the case where a working memory load and distractor predictability showed an interaction, we further tested the effect of predictability for 1- and 2-back trials separately. We also tested the effect of working memory load for predictable and unpredictable distractors, respectively.

5.2.7. Analysis of the brain-behaviour relationship

Lastly, we tested whether the neural measures of interest, i.e., CNV, SFN, and ALI, predicted behavioural performance. For each neural measure, we ran single-trial generalized linear mixed-effect models using logistic regression, with accuracy (0 = incorrect, 1 = correct) as the outcome variable and each neural measure as the predictor.

5.3. Results

5.3.1. The modulation of behavioural sensitivity by distractor predictability depends on the load

To understand how distractor predictability may exert influences on behavioural performance under different load conditions, we tested how behavioural sensitivity (d’) and criterion (c) were modulated by the factors SNR, working memory load, and distractor predictability using repeated measures ANOVAs on each of the behavioural measures separately.

For behavioural sensitivity (Figure 5.1C, left), the interaction SNR x working memory load x distractor predictability was significant ($F_{1,14} = 5.70$, $p = .03$, $\eta^2_p = 0.29$), suggesting that the modulation of memory performance by distractor predictability depended on both perceptual and cognitive load. Post-hoc analysis indicated that under the 2-back condition, the interaction between SNR and distractor predictability was close to significance ($F_{1,14} = 4.23$, $p = .06$, $\eta^2_p = 0.23$). Figure 5.1C shows that participants were more sensitive in the match between the current number and memory representation with unpredictable distractors when SNR is 0, but less sensitive with unpredictable distractors when the target had a lower intensity than the distractor (i.e., SNR = -10 dB).

For criterion (Figure 5.1C, right), participants performed more conservatively (i.e., a higher tendency of not responding) when the working memory load was high ($F_{1,14} = 12.72$, $p = .003$, $\eta^2_p = 0.48$). Other than that, there was no significant main effect of SNR, distractor predictability, or any interaction between the three factors (all $p > .06$).

5.3.2. Distractor predictability affects post-stimulus alpha lateralisation

To investigate whether alpha lateralisation was modulated by distractor predictability, we first demonstrated the existence of alpha lateralisation by comparing the attentional modulation index (AMI) between the left and the right hemispheres (Figure 5.2A). A positive AMI means higher oscillatory power in the attend-left versus attend-right conditions. A cluster permutation test (two-tailed) across time points found a close-to-significant cluster between 0.25 to 0.55 s post-stimulus onset ($t_{sum} = 18.68$, $p = .06$).

Second, we investigated whether alpha lateralisation differed in strength with distractor predictability (Figure 5.2B). We only probed into distractor predictability as it was the major interest of the current study. We thus collapsed across the other factors, SNR and working memory load, in this analysis. We calculated the alpha lateralisation index (ALI) for trials with predictable and unpredictable distractors, respectively, and analysed the ALI difference in the same time window of the close-to-significant cluster in the AMI analysis (i.e., 0.25 to 0.55 s). The posterior alpha power was more lateralised when the distractors were unpredictable versus predictable ($t_{14} = 2.40$, $p = .02$, Cohen’s d = 0.59). T-tests against zero (two-tailed) show that ALI with unpredictable distractors was significantly larger than zero ($t_{14} = 2.92$, $p = .01$, Cohen’s d = 0.75). ALI with predictable distractors, however, was not ($t_{14} = 1.18$, $p = .26$, Cohen’s d = 0.28).

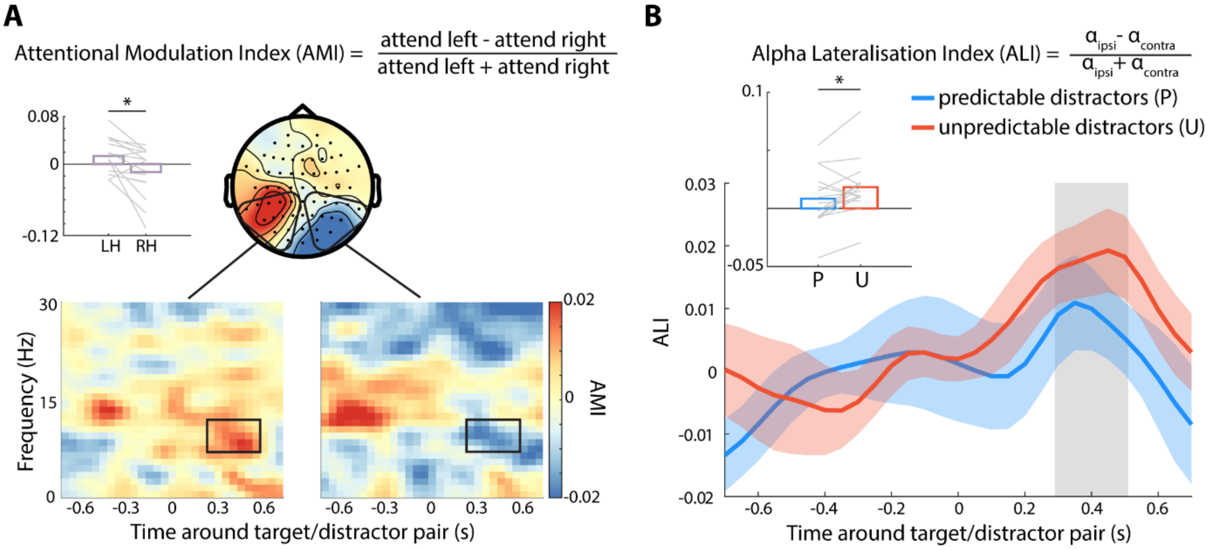

Figure 5.2. Results of alpha lateralisation by distractor predictability. A) Top panel shows the scalp map of the attentional modulation index (AMI) at the post-stimulus cluster and 8 – 12 Hz (outlined in black at the bottom panel). The bottom panel shows the time- and frequency-resolved AMIs at a subset of electrodes in the left (left column) and right (right column) hemispheres. With a priori electrodes and frequencies of interests, a cluster test showed that the AMI in left electrodes was more positive than the AMI in right electrodes between 0.25 to 0.55 s post target and distractor onset, which was close to significance (p = .06). Inset shows the comparison between AMI in the left and right hemispheres at the time window derived from the cluster test. Bars show averaged AMI across the a priori electrodes and frequencies, and across the time window indicated by the cluster test. Lines show data from individual participants. B) Time-resolved alpha lateralisation index (ALI) around target and distractor presentation. Lines show averaged ALI across participants for predictable (blue) and unpredictable (red) distractors. Shaded areas with the same colour show ±1 SEM across participants. The grey shaded area showed the time window of interest, which was derived from the previous cluster permutation test in the AMI analysis. Inset shows the averaged ALI across time for predictable and unpredictable distractors (bar). Grey lines show individual data. * p < .05.

5.3.3. Perceptual/cognitive load and distractor predictability modulate event-related potentials

Next, we investigated the effects of perceptual load, working memory load, and distractor predictability on different ERP components (Figure 5.3). We focused on sustained frontal negativity (SFN), contingent negative variation (CNV), N1, and P2.

The SFN amplitude (Figure 5.3A) was modulated by the interaction between working memory load and distractor predictability (β = -0.02, SE = .006, t_{28199} = -2.93, *p* = .003), as well as the main effect of the two factors (working memory load: β = 0.03, SE = .006, t_{28199} = 4.38, *p* < .001; distractor predictability: β = -0.01, SE = .006, t_{28199} = -2.53, *p* = .01). Specifically, when the distractors were predictable, the SFN amplitude was smaller when participants performed a 2-back task than when they performed a 1-back task (β = 0.045, SE = .008, t_{14103} = 5.42, *p* < .001). In the 2-back condition, the SFN amplitude with predictable distractors was smaller than with unpredictable distractors (β = -0.032, SE = .008, t_{14103} = -3.83, *p* < .001). Furthermore, SFN amplitude was smaller with high perceptual load, as shown by the main effect of SNR (β = -0.013, SE = .006, t_{28199} = -2.30, p = .02). The other interaction terms were not statistically significant (all p > .35).

For the CNV slope (Figure 5.3B), we also found an interaction between working memory load and distractor predictability (β = -0.01, SE = .006, t_{28199} = -1.99, p = .046). Specifically, the CNV slope was only larger in the 2-back condition versus the 1-back condition when the distractors were unpredictable (β = -0.02, SE = .008, t_{14100} = -2.50, p = .01). We observed no such effect between 2- and 1-back with predictable distractors (β = 0.002, SE = .008, t_{14100} = 0.30, p = .77). All the other main effects and interactions were not significant (all p > .1).

The perceptual load had an influence on the early ERPs N1 (Figure 5.3C) and P2 (Figure 5.3D). For both N1 and P2, the amplitude was larger when the target stream was presented at the same intensity (i.e., 0 dB) as the distractor stream, compared with when the target stream was at a lower intensity (N1: β = -0.02, SE = .006, t_{28199} = -2.82, p = .005; P2: β = 0.03, SE = .006, t_{28199} = 4.33, p < .001). There was no other significant main effects or interaction between the two ERP components (all p > .1).

In sum, distractor predictability had an interactive influence on slow neural activities both before and after target/distractor onset, together with working memory load. The interactions were driven by larger neural responses in the unpredictable 2-back condition compared with other conditions. SNR had an impact on the stimulus-driven ERP components such as N1 and P2 and did not interact with distractor predictability or working memory load.

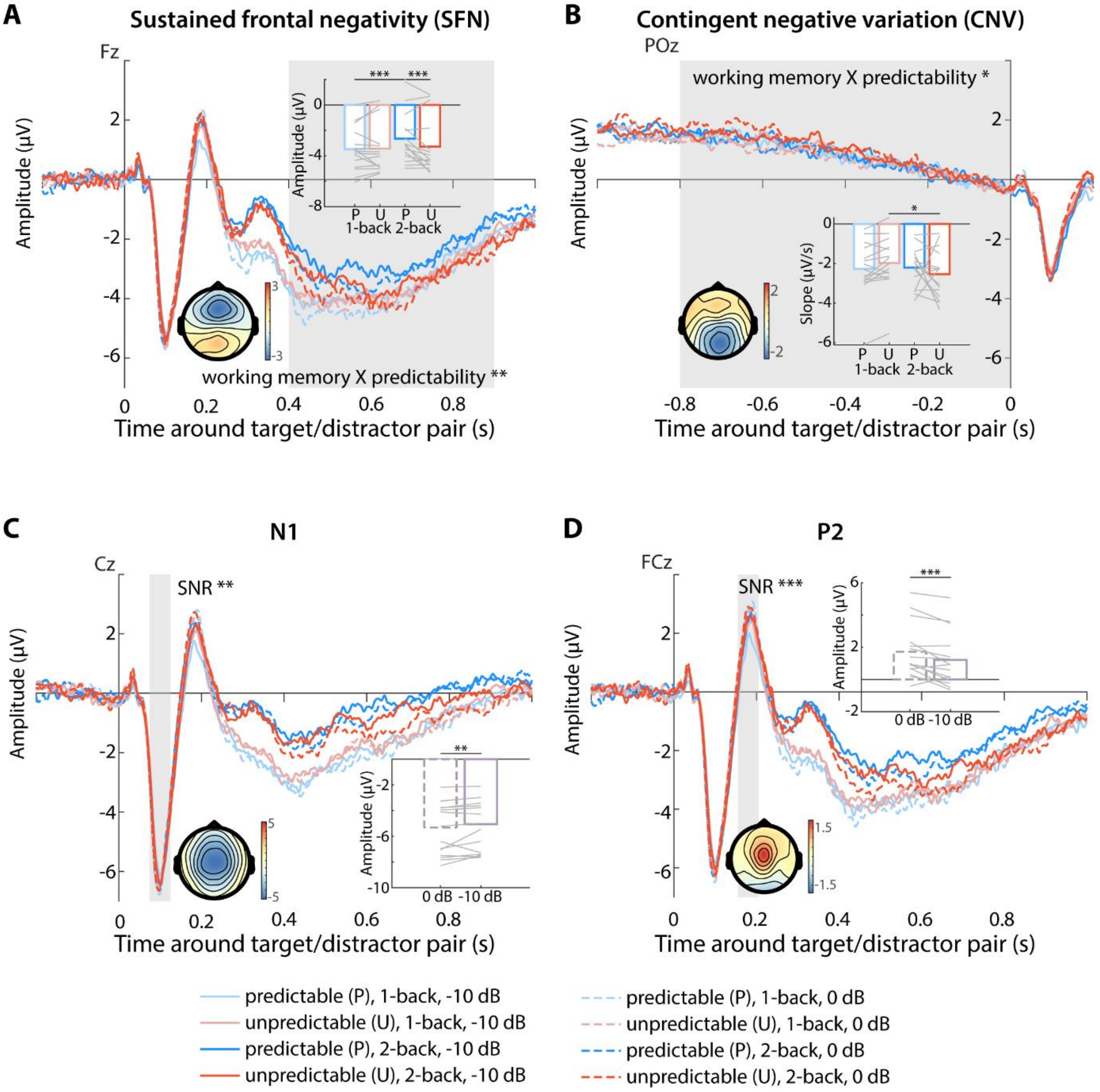

Figure 5.3. Grand-average event-related potential (ERP) waveforms for Fz (A), POz (B), Cz (C), and FCz (D). Each electrode represents the peak effect of the respective ERP component. Grey shaded areas indicate the time window in which the ERP component was extracted. Left insets show the scalp maps for each ERP component within the time window of interest. Right insets show the major results for each component. Bars indicate averaged ERP amplitude or slope across participants, while grey lines show individual ERP amplitudes or slopes. ERP amplitudes or slopes shown in the bars were extracted from the peak electrode and its two adjacent electrodes. * p < .05. ** p < .01. *** p < .001.

5.3.4. Pre-stimulus neural activity predicts behavioural sensitivity

Last but not least, we probed into the brain-behaviour relationship by relating the strength of each neural measure, CNV, sustained frontal negativity (SFN), and ALI, to accuracy in the n-back task. To this end, we used a generalised linear mixed-effects model using logistic regression (i.e., logit link function) to regress accuracy on the strength of neural measures. CNV slope significantly predicted accuracy (β = -0.08, SE = .03, t_{28205} = -2.73, p = .006), in that a more negative CNV slope is associated with better performance (Figure 5.4). For post-stimulus neural measures, however, neither SFN ($\beta = 0.02$, SE = .03, $t_{28205} = 0.77$, $p = .44$) nor ALI ($\beta = -0.007$, SE = .03, $t_{28205} = -0.25$, $p = .8$) predicted the behavioural outcome.

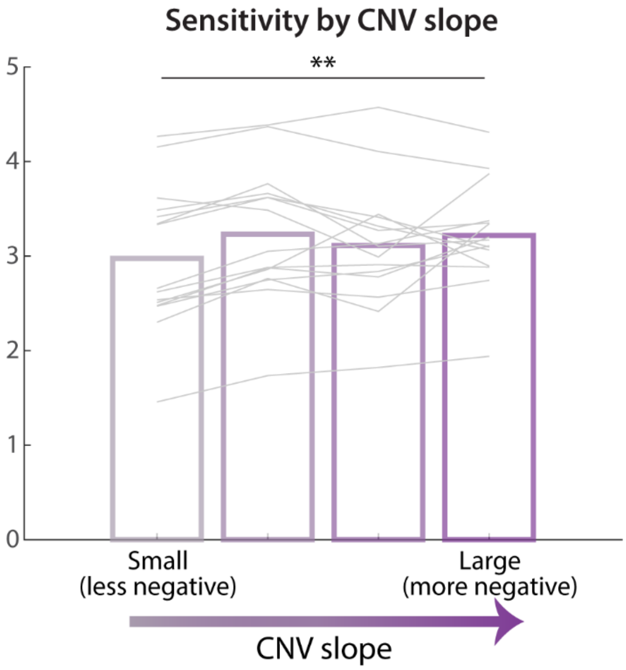

Figure 5.4. Brain-behaviour relationship between pre-stimulus CNV slope and behavioural sensitivity. A more negative CNV slope is related to better behavioural performance. For visualisation purposes, trials were binned according to the strength of the CNV slope. Behavioural sensitivity was calculated across trials within each bin. Bars show averaged behavioural sensitivity across participants. Grey lines show individual behavioural sensitivity. Statistical testing was done on the single-trial level by regressing accuracy on the CNV slope using logistic regression in the generalised linear mixed-effects model. ** p < .01.

5.4. Discussion

The current study elucidated the potency of predictable versus unpredictable distractors to interfere with the behavioural and neural responses in a working memory task. Behaviourally, distractor predictability interacted with both SNR and working memory load in its influence on participants' memory performance. Neurally, post-stimulus alpha lateralisation was higher when the distractors were unpredictable; distractor predictability and working memory load had an interactive influence on pre- and post-stimulus sustained ERP responses. These preliminary results suggest that expectation can be formed solely by local transition probability in the to-be-suppressed distractors and modulates the degree to which the distractors permeate through the attentional filter.

5.4.1. Local statistics of distractors play a role in the ultimate distraction

The current study is among the first few studies (Bogaerts et al., 2022; Southwell et al., 2017) that probe into how the ultimate distraction could be influenced by the local transition probability free from the influence of global statistics. Note that in a general sense, global probability (i.e., item frequency) is subsumed within transition probability as transition probability entails both item repetition, which would be concomitantly higher with higher probability, and item alternation (Meyniel et al., 2016). In the current study, by equating the global probability of each distractor number (25%) in both predictable and unpredictable conditions, the only difference between predictable and unpredictable distractors rests within the local transition probability of the next distractor given the identity of the current number. The difference in behavioural performance with predictable versus unpredictable distractors can thus be attributed to expectation formed from the local predictability in the distractor stream.

The interactive effect of distractor predictability on behavioural sensitivity deviates from the conclusion derived from studies on the global probability of distractors, which states that more predictable distractors reduce their potency to distract (van Moorselaar & Slagter, 2020). It could be due to the difference between the strength of expectation generated from local predictability and that from global probability (Meyniel et al., 2016). It takes fewer trials to extract statistical regularities in terms of repetition (e.g., predicting "A" from the sequence "A-A") compared with alternation (e.g., predicting "A" from the sequence "A-B-A-B"). The expectation built from global probability, which involves item repetition, may thus be stronger than the expectation built from local transition probability, which involves both repetition and alternation. Alternatively, the human brain may use different systems to build expectations based on global versus local statistics. The local and global probability were said to be implemented in different neural networks (Arjona et al., 2018). The difference in the underlying neural implementations of global and local predictability may give rise to the difference in their effect on distractor interference. Future studies may test the neural correlates of the global versus local distractor expectation to resolve the influence of expectation derived from different levels of statistics.

The interactive influence of distractor predictability with perceptual/cognitive load may potentially reconcile the inconsistent evidence on local distractor expectation. Broadly speaking, the results in the current study are consistent with the load theory of attention, in that the exact influence of distractor predictability may depend on the perceptual load or cognitive load in a study. Whether distractor predictability was beneficial to target-related performance may depend on the study design, such as whether the perceptual load was high (Southwell et al., 2017) or whether the participants were cognitively taxed (Hunter & Pisoni, 2018). More data are needed for a solid conclusion on how distractor predictability interacts with perceptual and cognitive load.

While behavioural performance is not always better with predictable distractors in the current study, it does not necessarily imply that the current results speak against the expectation suppression account. The ultimate degree of distraction is a consequence of a cascade of neural responses associated with distraction. Expectation suppression is based on the theoretical predictive processing account which concerns the modulation of neural responses by stimulus expectation (Noonan et al., 2018). We should take into account the neural components of distraction to arrive at a more comprehensive picture.

5.4.2. Distractor expectation reduces reactive distractor filtering

Alpha lateralisation was most prominent in the post-stimulus time window in the current study (i.e., 0.25 to 0.55 s), which may serve as a reactive inhibition of external distraction. Alpha lateralisation has mainly been associated with preparatory selective attention, which was supported by an increase in alpha lateralisation in the cue-stimulus interval (Haegens et al., 2011; B. Wang et al., 2019; Wöstmann & Obleser, 2016). However, its strictly proactive role in selective attention has recently been questioned (Antonov et al., 2020; van Diepen et al., 2016). Instead of merely concerning the preparatory selection of task-relevant events, alpha lateralisation may also be involved in reactive stimulus processing or filtering, which is manifested as an increase in alpha lateralisation in the post-stimulus time window. Several studies have demonstrated post-stimulus alpha lateralisation in visual attention (Bacigalupo & Luck, 2019; van Diepen et al., 2016), auditory attention (Klatt et al., 2018a, 2018b), in the absence of a spatial cue (Klatt et al., 2018a), or when spatial information was held in working memory (Klatt et al., 2018b). As the task in the current study involved working memory, it is possible that the post-stimulus alpha lateralisation subserves the selection and suppression of the internal working memory representation based on task relevance after stimulus onset.

What role does distractor predictability play in attentional selection indexed by alpha lateralisation? Previous studies aiming at understanding how distractor expectation modulates alpha lateralisation ascribed alpha lateralisation as a preparatory response to the upcoming distraction, and thus focused on the pre-stimulus interval (van Moorselaar et al., 2020; B. Wang et al., 2019). In the current study, post-stimulus alpha lateralisation was only observed with unpredictable distractors. Instead of not having an influence at all, distractor predictability's influence on distractor filtering may be more evident in the reactive stage of stimulus processing. The strength of external distraction was found to increase alpha responses (Bonnefond & Jensen, 2012). Distractors that are unpredictable may be more difficult to be ignored, leading to enhanced reactive suppression.

We found no pre-stimulus alpha lateralisation in the current study, which was consistent with the previous studies examining expectation with fixed visual features (Noonan et al., 2016; van Moorselaar et al., 2020). Only one previous study found a pre-stimulus alpha lateralisation effect with distractor expectation; this study differed from the other studies in that only distractor location was predictable (B. Wang et al., 2019). In the current study, participants may rely less on spatial expectation as they could also employ feature-based expectation for distractor suppression, resulting in a less profound pre-stimulus alpha lateralisation which was associated mainly with spatial attention (van Moorselaar et al., 2020). Alternatively, the absence of pre-stimulus alpha lateralisation may be due to the sustained attention across the whole block. Previous studies found alpha lateralisation at its peak after cue onset and could still be observed after the first stimulus onset (Tune et al., 2018; Wöstmann et al., 2021). As participants only had to focus their attention on one side throughout the whole block, the pre-stimulus alpha lateralisation may have tapered off over time, and thus not evident in the time window before each presentation of the target and the distractor.

5.4.3. Distractor expectation indirectly influences higher-order cognitive operations

The interactions between distractor predictability and cognitive load on slow ERP responses, namely, sustained frontal negativity (SFN) and CNV, suggest that distractor expectation formed by local transition probability indirectly influences higher-order cognitive operations such as attentional selection and working memory. Both pre- (Kononowicz & Penney, 2016) and post- (Kaiser, 2015) stimulus slow neural activities are said to reflect higher-order cognition such as optimisation for the upcoming cognitive operation and working memory, respectively. In the current study, the neural responses with unpredictable distractors and high cognitive load were larger compared with neural responses in a subset of other conditions. For instance, in the 2-back condition, the SFN amplitude was larger for unpredictable distractors versus predictable distractors. The CNV slope with unpredictable distractors in the 2-back condition was larger than that in the 1-back condition. Distractor predictability may reduce the cognitive resources employed during a difficult task.

Sustained slow wave activity in the anterior electrodes may reflect the post-stimulus cognitive operations essential to the current working memory task, such as working memory updating or distractor interference in working memory. Post-stimulus sustained activities such as frontal negativity (Schneider et al., 2020) or delta power (Rac-Lubashevsky & Kessler, 2018) have been ascribed to the updating or maintenance of working memory representation. In the face of distraction, individuals with higher versus lower working memory capacity showed a different sustained response (Vogel et al., 2005); individuals with a frontal lesion showed a larger SFN when compared with healthy control (Chao & Knight, 1998). With regard to predictive processing, previous studies also found a modulation in sustained negative response by contextual (Coderre et al., 2020) or semantic predictability (León-Cabrera et al., 2019). Given the association with different cognitive operations, the modulation of sustained negativity in the current study may arise from the change in shielding working memory representation by distractor interference due to the predictive processing of the distractors.

Here, participants needed to both update the working memory representation and shield the representation from external distraction in order to successfully perform the task. In addition, they may make use of the predictability in the distractor sequence to optimise the attentional selection and working memory processes. As distractor predictability had both a main effect and interaction effect on sustained frontal negativity, we hereby speculate that distractor expectation, as formed by local transition probability, reduces the resources needed for the prediction making process. Distractor expectation may reduce the potency of a distractor to interfere with the working memory update or maintenance.

Apart from the post-stimulus neural response, distractor predictability also showed an indirect influence on pre-stimulus neural activity, suggesting that distractor expectation may play a role in the preparatory attentional selection. Traditionally studied as a correlate of motor timing (Walter et al., 1964), CNV has been theorised as a process of resource optimisation by a change in the brain's excitability (Kononowicz & Penney, 2016). CNV is also associated with the allocation of attentional resources under different degrees of distraction (Wöstmann et al., 2015), and is related to attention capacity (Kropp et al., 2001). In a previous study on temporal orienting (Capizzi et al., 2013), CNV amplitude was also modulatory by stimulus history (i.e., the timing information of the previous trial) and cognitive load (i.e., single versus dual task). The current study found that the CNV slope was stronger in 2-back versus 1-back condition only when the distractors were unpredictable. It is conceivable that only with distractors that are difficult to ignore do participants need stronger attentional selection in a more difficult task (i.e., 2-back task).

We found that pre-stimulus neural activity explains the ultimate behavioural performance. Specifically, a larger CNV slope corresponded to a higher perceptual sensitivity. The results are along the line with some studies relating CNV with behavioural responses (Hillyard, 1969; Hillyard et al., 1971; McAdam & Rubin, 1971; see however Perdok & Gaillard, 1979). The brain-behaviour relationship found in the current study suggests that more preparatory effort is beneficial to attentional selection, and ultimately behavioural performance.

Through its own or interaction with the working memory load, predictable distractors led to reduced neural signatures of higher-order cognition in general. These results are largely consistent with the expectation suppression account. While larger post-stimulus sustained activity (i.e., SFN) was associated with higher proneness to distraction (Chao & Knight, 1995, 1998), larger ipsilateral increase and contralateral decrease in alpha activity were associated with higher distractor suppression (Haegens et al., 2012). It is possible that predictable distractors reduce both the proneness to distraction and the ability to suppress distraction. The relative contribution of the proneness to distraction and distractor suppression thus gives rise to differential behavioural outcomes under different load and predictability conditions. Of note, the current study did not test the proneness to distraction and distractor suppression separately. Further studies which allow the differentiation of the two processes should be done to elucidate the contribution of distractor predictability on each of the respective cognitive operations.

5.4.4. The interference by distractor expectation does not hinge on perceptual load

While perceptual load modulated the amplitude of the stimulus-evoked early ERPs (i.e., N1 and P2), it did not interact with neither cognitive load nor distractor predictability on the neural level. The absence of interaction is surprising, given that perceptual load interacted with the other factors on the behavioural level. The lack of modulation is also inconsistent with the load theory of attention, according to which distractor interference is more prominent with low perceptual load. We hereby speculate on two possible reasons why perceptual load did not have a strong influence on neural responses.

First, it is possible that perceptual load simply does not play a role in auditory distraction. Although numerous studies in the visual modality supported the notion that perceptual load modulated distractor interference (de Fockert et al., 2001; Gutteling et al., 2022; Lavie & De Fockert, 2003), the corresponding evidence in the auditory modality is less clear (S. Murphy et al., 2017). With different manipulations of auditory perceptual load, previous studies failed to find concurring evidence of its influence on distractor processing (Gomes et al., 2008; Melara et al., 2021; S. Murphy et al., 2013). Melara et al. (2021) speculated that studies of visual and auditory perceptual load differed in that in visual studies, the perceptual load was usually manipulated in a selective paradigm where participants had to locate the task-relevant stimulus among the other stimuli. In auditory studies, participants had to focus on the task-relevant stimulus and filter out the task-irrelevant ones. The selective versus filtering nature of selective attention studies in different modalities may lead to its different sensitivity to the modulation of perceptual load.

Second, the manipulation of perceptual load in the current study may not be drastic enough to interfere with distractor processing. The current study manipulated perceptual load by signal degradation (i.e., lower intensity in the target stream), which was found to modulate distractor interference in the visual modality (Gutteling et al., 2022). However, the translation of such manipulation from visual to auditory modality may have weakened its modulatory influence. Previous studies attempted to reveal the influence of perceptual load on distraction by manipulating perceptual similarity (Melara et al., 2021; S. Murphy et al., 2013, experiment 1), inter-stimulus interval (Gomes et al., 2008), and task difficulty (S. Murphy et al., 2013, experiment 2). However, the perceptual load effect on distractor processing did not support the perceptual load theory in these studies. The effect may be only evident in a subset of tasks or stimuli, which could be further examined in future studies.

5.5. Conclusion

In summary, the current study demonstrated that distractor predictability based on local statistics modulated the ultimate degree of distraction. On the behavioural level, distractor predictability interacted with both cognitive and perceptual task demands in their influence on the working memory representation of the to-be-remembered target. On the neural level, higher distractor predictability diminishes reactive filtering of distraction and potentially has an interactive impact on attentional selection or working memory maintenance. These results demonstrate that the final degree of behavioural distraction may be subject to distractor expectation by the relative suppression of neural responses, which are associated with different cognitive operations which may be facilitatory or detrimental to the filtering of the distractor. The interplay between the neural responses subserving different cognitive operations may give rise to a dynamical modulation of behavioural distraction by distractor expectation.

6. General discussion

With three empirical studies, the present thesis investigates the behavioural and brain dynamics of distraction. The major goal of this thesis is to elucidate the temporal mechanisms underlying distraction. While detailed discussions for each aspect of the temporal mechanisms can be found in the discussion sections of each study, I will review the essential topics of this thesis from a broader perspective. I will first examine how each study in this thesis may or may not elucidate the different components of distraction by revisiting the distraction framework. Second, I will discuss the extent to which distraction is dynamic. Third, I will argue that behavioural evidence is of primary importance in the study of distraction. Finally, I will discuss the methodological concerns in studying behavioural rhythms in the current literature.

6.1. Summary of the experimental results

Study 1 investigated the temporal dynamics and neurobiological basis of distractibility. Specifically, EEG was recorded while participants performed a pitch discrimination task with an auditory distractor which occurred unexpectedly in time. Behavioural sensitivity and distractor-evoked neural response were found to wax and wane across distractor onset time between 3 and 5 Hz, demonstrating that the ultimate degree of distraction fluctuates in a subsecond temporal scale. Furthermore, the neural phase of theta oscillations prior to distractor onset explained the fluctuations in behavioural sensitivity in the inferior frontal and insular cortex regions. Control analyses using trials without a distractor showed an absence of such an effect, reinforcing that the behavioural and brain dynamics are specific to distractor-related processes. These results showed that the periodic brain oscillations in regions associated with cognitive control of working memory are tightly linked to fluctuating distractibility.

Study 2 set out to elucidate whether distractibility can be entrained. We ran 4 behavioural experiments and 1 control experiment to systematically search for the temporal regularity effect on the proneness to distraction by using different variants of the irrelevant sound task (Colle & Welsh, 1976; Salamé & Baddeley, 1982). Temporal irregularity was operationalized by a violation of a regular tone sequence (Experiment 1), and by irregular onset-to-onset delays in sequences of tone (Experiment 2) or speech items (Experiments 3&4), respectively. In all experiments, the temporal regularity of distractors did not influence participants' memory recall or recognition performance. Instead, the temporal regularity of distractors modulated secondary performance metrics: The motor response was faster

(Experiment 3) and participants were more conservative in reporting a “match” between the probe and the item in memory (Experiment 4). The present results demonstrate that the temporal regularity of the task-irrelevant inputs does not necessarily affect the precision of memory representations (i.e., accuracy) but rather the response behaviour (e.g., response speed and bias).

Study 3 aimed at exploring the behavioural and brain dynamics of distractor predictability. Essentially, we examined the potential factors modulating the influence of distractor predictability on working memory performance and explored the potential neural correlates of distractor expectation with a behavioural and electrophysiological study. In a working memory task where participants had to match the current number with a previously presented number, participants had to attend to one number stream from one side (i.e., attended stream) and ignore the number stream from the other side (i.e., ignored stream). In the attended stream, perceptual load and cognitive load were manipulated by the stimulus intensity and working memory load, respectively. In the ignored stream, distractor predictability was manipulated by the local transition probability within the number sequence while holding the global probability (i.e., item frequency) of the numbers equally probable. Behavioural results showed an interaction between distractor predictability, perceptual load, and cognitive load: Distractor predictability had a different influence on behavioural sensitivity under different perceptual and cognitive load conditions. Neurally, distractor predictability reduced post-stimulus alpha lateralisation, a well-received neural correlate of attentional filtering. On top of that, distractor predictability interacted with cognitive load in its modulation of pre- and post-sustained neural responses. These results suggested that distractor expectation derived from local statistics shapes the potency of a distractor to interfere with working memory performance.

6.2. The components of distraction revisited

Distraction is a multi-faceted construct. The behavioural measure of distraction captures the final detriment arising from different underlying distractor-related processes. Although it is crucial to measure behavioural performance to understand the disruptive influence of a distractor, a behavioural response only provides one measure of the final distraction and does not inform of the potential contributions from the different underlying components of distraction. By means of experimental design and neuroimaging methods, some components can be studied in isolation from the other distractor-related processes (Wöstmann et al., 2022). In this section, I will first recap the essential components of distraction. Then, I will discuss how different components may contribute to the final degree of distraction in each study.

Aside from the external factors such as distractor strength and the cognitive load of a task, the final degree of distraction mainly depends on two endogenous factors: distractibility and distractor suppression. The variability of distractibility in an experiment has often been neglected as it is considered to only unfold in relatively long temporal scales such as in years (K. L. Campbell et al., 2012; Kannass et al., 2006). It is suggested to change with age and is associated with the frontal cortex. Distractibility was studied cross-sectionally by comparing between age groups (K. L. Campbell et al., 2012; Chadick et al., 2014) and between patients with frontal lesions and healthy control (Chao & Knight, 1995, 1998). Researchers have recently acknowledged the need to tease apart the different types of distractor suppression (Noonan et al., 2018; Schneider et al., 2021; Wöstmann et al., 2022). For instance, active, independent distractor suppression is recommended to be separated from the automatic deselection of task-irrelevant events collateral to target selection (Schneider et al., 2021). The brain may be engaged in proactive suppression, which involves a preparatory inhibition of anticipated distractors, or reactive suppression, which refers to the reactive disengagement of a distractor that is often salient (Geng, 2014; Wöstmann et al., 2022).

While the present thesis is primarily concerned with the temporal dynamics of distraction, each study positioned itself differently within the framework of distraction. Of note, not all of the studies here aimed at dissociating one component of distraction from the others. In all studies, distractibility and distractor suppression both contributed to the ultimate degree of behavioural distraction. In the following, I will review how distractibility and distractor suppression may play a role in each study. In some studies, the differentiation between the components was more subtle. I will rely on reverse inference in such a case and speculate on the possible underlying mechanisms.

In Study 1, we were able to isolate distractibility from distractor suppression processes by using distractors that occurred unexpectedly, both in terms of whether or when they would occur. We could capture the variability in distractibility within an individual, which fluctuates in a second. Note that the conclusion of fluctuating distractibility does not solely come from the cyclical modulation of behavioural or neural time courses by distractor onset time (Figure 3.2). As both the behavioural sensitivity and distractor-evoked neural responses were post-distractor measures, they may reflect both distractibility and distractor suppression.

The conclusion that distractibility, but not distractor suppression, fluctuates in Study 1 is mainly based on the following reasoning. First, as the distractor was presented in only half of the trials and randomly across possible distractor onset times, participants could not anticipate the occurrence of a distractor in a given trial and thus could not engage in proactive suppression. Second, the phasic relationship between neural oscillations and the behavioural measure of distraction was specific to the pre-distractor time window, which speaks against the hypothesis that the fluctuations in the final degree of distraction come from the fluctuations in post-stimulus distractor processing such as reactive suppression. Lastly, the task difficulty and distractor strength were not manipulated in Study 1, avoiding the influence of these exogenous factors on the variability in distraction.

In contrast, Study 2 was purely a behavioural study and thus did not include neural measures which are typically associated with distractibility (e.g., frontal activation; L. L. Chao & Knight, 1995) nor distractor suppression (e.g., alpha lateralisation; Worden et al., 2000). We conducted a purely behavioural study as the main interest of Study 2 was to push the extent to which temporal regularity plays a role in the primary (i.e., accuracy) and secondary (e.g., speed, confidence) performance metrics.

Which component(s) of distraction would Study 2 be probing into if there were meaningful behavioural evidence of a temporal regularity effect of distractor? Entrainment describes the temporal alignment of an oscillatory system in accordance with another exogenous oscillatory system (Lakatos et al., 2019). It is possible that temporally regular distractors would temporally align the distractibility dynamics found in Study 1, so that the distractors could occur at an optimal phase of distractibility. Alternatively, temporally expected distractors may facilitate proactive suppression of the anticipated distractor (Gresch et al., 2021). The difference between the two hypotheses lies in whether the temporally regular distractors would modulate the general proneness to all distractors or only to the specific distractor which is anticipated.

Study 3 explored the influence of distractor predictability on a cascade of neural responses. As we did not aim to distinguish between distractibility and distractor suppression, both may contribute to the ultimate degree of distraction. With its endogenous fluctuations, distractibility may explain some variations within the behavioural consequence of distraction. The fluctuations in distractibility, as it is endogenous (Study 1) and not modulated by external temporal regularity (Study 2), may impact the behavioural detriment of distraction randomly across all conditions.

It is plausible that distractor suppression and the exogenous factor cognitive load jointly played a role in explaining the ultimate degree of distraction in Study 3. While distractor predictability was hypothesised to engage proactive suppression of the distractor, the timing in which the influence of distractor predictability becomes evident is still under debate (van Moorselaar & Slagter, 2020). In previous studies of visual attention, distractor predictability was found to modulate neural responses which are typically associated with reactive filtering (P_D; van Moorselaar et al., 2021; Wang et al., 2019). The decrease in post-target/distractor pair alpha lateralisation with high distractor predictability suggests that reactive distractor filtering may be influenced by distractor expectation. Furthermore, distractor expectation and cognitive load may jointly influence the potency of a distractor to distract via modulating the preparatory and reactive processes of selective attention (Wöstmann et al., 2015) and working memory (Schneider et al., 2020) as shown in the modulation of sustained neural responses.

All in all, while distractibility and distractor suppression jointly contributed to the ultimate detriments of distraction, they may have played different roles in the 3 studies in the present thesis. Note that in all 3 studies, we did not distinguish active suppression from automatic suppression as we did not implement a proper baseline condition to delineate between the two. A neutral stimulus with which no distractor suppression is needed would further our understanding of how active distractor suppression would play a role in the unfolding of distraction in time.

6.3. The temporal dynamics of distraction

Why is it important to study the temporal dynamics of distraction? The current research on dynamics in cognition mainly focuses on the processing of task-relevant targets and neglects the potential dynamics in the processing of task-irrelevant distractors (Buschman & Kastner, 2015; Schroeder & Lakatos, 2009). The human brain is ubiquitous in its oscillatory signatures (Buzsáki & Draguhn, 2004), which is closely tied to the behavioural dynamics of attention (Fiebelkorn & Kastner, 2019; Haegens & Zion Golumbic, 2018). However, the oscillatory dynamics of the brain are not limited to attention-related networks (A. Keitel & Gross, 2016). How the brain dynamics outside of the attention-related network are associated with the behavioural dynamics of the cognitive processes outside the spotlight of attention remains unknown. The present thesis investigates the temporal mechanisms of distraction, namely, the endogenous fluctuations of distractibility (Study 1), entrainment by temporally regular distractors (Study 2), and distractor expectation formed by local statistics (Study 3). Together, the 3 empirical studies set the boundary to which distraction exhibits temporal dynamics.

6.3.1. The endogenous and exogenous rhythms of distraction

The proneness to distraction is inherently dynamic but cannot be entrained, according to the results from Studies 1 and 2 (Figure 6.1).

The ebbing and flowing of distractibility found in Study 1 urge for an extension of the theoretical formulation of the blinking attentional spotlight. The blinking spotlight of attention posits that attentional sampling waxes and wanes over time as if the attentional spotlight is blinking regularly (Buschman & Kastner, 2015; VanRullen et al., 2007). The cyclical fluctuations of attention were hypothesised to originate from the cyclical fluctuations of neural excitability in the perceptual/attentional neural network (Fiebelkorn & Kastner, 2019; VanRullen, 2016). Under this framework, anything outside of the attentional spotlight is invisible and implicitly assumed to be static.

Study 1 showed that contrary to what is originally assumed, the “invisible” realm outside the attentional spotlight is also blinking. The orchestration between the brain and behavioural dynamics of distraction in theta-like cycles reveals the pervasiveness of rhythmic cognition beyond target selection. Of note, it is still unclear whether the brain dynamics in the brain regions responsible for the fluctuations in the attentional spotlight and distractibility are independent of each other. It is also possible that the synchronisation between the frontoparietal attention network, the neuronal network associated with rhythmic attention (Helfrich et al., 2018), and the left inferior frontal/insula cortical regions found in Study 1 gives rise to the distractibility dynamics.

The results in Study 2 converge with the view that entrainment requires attention (Lakatos et al., 2019). Entrainment was said to be instrumental to the sensory selection of task-relevant events (Haegens & Zion Golumbic, 2018; Schroeder & Lakatos, 2009), and was proposed to be controlled by attention. Lakatos et al. (2019) proposed that entrainment serves as a mechanism to prioritise task-relevant rhythmic inputs by amplifying the neural response to the selected input while diminishing the influence of task-irrelevant inputs. The absence of evidence in the primary performance metrics in Study 2, with the support of Bayesian statistics, is consistent with this view.

The modulatory influence of the temporal regularity of distractors on the secondary performance metrics suggests that the exogenous rhythm in distractors may not go unnoticed. Participants seemed to lean towards the preferred response behaviour when the distractors were temporally regular, resulting in a faster response (Experiment 3, Study 2) and more conservative bias (Experiment 4, Study 2). The periodicity in temporally regular distractors may facilitate motor preparation (Morillon et al., 2016). The disruptive influence of temporal irregularity in distractors may be small and only manifested in measures that are more sensitive to small disruptions such as metacognitive measures (Kattner & Bryce, 2021).

Studies 1 and 2 shed light on the extent to which distraction is related to the endogenous (i.e., brain) and exogenous (i.e., distractor regularity in time) dynamics. Figure 6.1 illustrates the similarity and differences between target processing (Fiebelkorn et al., 2013; Henry et al., 2014; Ho et al., 2017; Hsu et al., 2014; Rohenkohl et al., 2012) and distractor processing in terms of the endogenous and exogenous dynamics. While rhythmic cognition within and outside of the attentional spotlight is a general phenomenon concomitant to neural dynamics, entrainment serves as amplification and adjustment of such rhythms specific to the attentional spotlight.

6.3.2. The role of temporal and feature-based expectation in distraction

Expectations built by local transition probability (Study 3), but not temporal regularity (Study 2), modulated the potency of the distractors to interfere with the working memory performance (Figure 6.1). These results raise the question: To what extent does distractor expectation play a role in the interfering influence on task performance?

Distractor expectation by temporal regularity may only have a subtle influence on cognitive operations needed in a working memory task, based on the results of the primary and secondary performance metrics in Study 2. In previous studies, violation of temporal regularity in the task-irrelevant stream elicited a mismatch brain response (e.g., Jacobsen & Schröger, 2003; Yabe et al., 1997), suggesting that the temporal regularity embedded in task-irrelevant events can be detected by the brain. By presenting distractors with or without temporal regularity simultaneously with temporally regular targets, Makov & Zion Golumbic (2020) showed that the change detection performance was better with unmasked targets when the distractors were temporally regular. While temporally anticipated distractors have been shown to lessen the overall interference to task performance (Menceloglu et al., 2017; van Ede et al., 2018), Gresch et al. (2021) directly tested how temporally predictable distractors, with fixed temporal occurrence relative to the target, facilitate the shielding of memory representation from external interference. The studies using the irrelevant sound paradigm, however, showed mixed results on the influence of temporal regularity on distractor interference (e.g., D. M. Jones & Macken, 1995; Parmentier & Beaman, 2015).

Drawing from the results of other empirical studies, the subtle influence of temporal expectation in Study 2 may be due to its lack of temporal contingency with the targets. In the aforementioned studies where temporal expectation facilitated performance (Gresch et al., 2021; Makov & Zion Golumbic, 2020; Menceloglu et al., 2017), temporally predictable distractors were also temporally contingent on the targets. For example, in Gresch et al. (2021), the predictable distractors were fixed in terms of their interval from the target. In Makov & Zion Golumbic (2020), temporally regular distractors also shared a predictable temporal relationship with the target. Specifically, the temporal relationship between the target (presentation rate at 1.6 Hz) and the distractor (2 Hz) changed periodically at the beat frequency of the two streams (0.4 Hz). The temporal contingency between the target and distractor may provide more information on the temporal occurrence of the upcoming probe (Gresch et al., 2021) or target stimulus (Makov & Zion Golumbic, 2020), thereby facilitating task performance. In Study 2, although the distractor sequence is temporally regular, the onset of the distractor sequence after target offset was random across trials to avoid the potentially confounding effect of temporal contingency. The lack of temporal regularity effect in Study 2 may thus be explained also as the lack of temporal contingency effect. Future studies could test the role of temporal contingency between the target and distractor to delineate its effect from the temporal regularity effect of distraction.

Distractor expectation by local transition probability, on the other hand, has an indirect influence on the final degree of distraction, as shown by the interaction between distractor predictability and task demands in Study 3. Similar to temporal expectation, feature-based regularity in task-irrelevant events could also be detected by the brain (Näätänen & Michie, 1979). The brain responds to the violation of various types of regularity ranging from stimulus repetition (Lui et al., 2021; Sams et al., 1983) to transition probability (Koelsch et al., 2016; Mittag et al., 2016). Apart from violation, the brain also responds to the formation of regularity in that neural responses to external events were upregulated if the events were predictable (Barascud et al., 2016; Dürschmid et al., 2018).

While expectation suppression is a well-received account in explaining distractor expectation’s impact on distractor processing (Noonan et al., 2018; van Moorselaar & Slagter, 2020), further understanding of the explanatory scope of expectation suppression on how distractor predictability worsens or ameliorates distractor interference is warranted. One major consideration is whether expectation suppression is limited to explaining behavioural evidence, neural evidence, or both. The neural results in Study 3 are consistent with the expectation suppression account, in that the neural responses are diminished when the distractors were predictable, especially for alpha lateralisation and post-stimulus frontal sustained responses. On the behavioural level, however, the direction in which distractor expectation influenced behavioural performance differed across perceptual and cognitive load conditions.

Psychological suppression should not be confused with neural suppression (Schneider et al., 2021; Wöstmann et al., 2022), as a psychological phenomenon is often a consequence of multiple underlying neurobiological components (Miller, 2010; Waschke et al., 2021). In research on distractor expectation, the theoretical backbone of the expectation suppression account is mainly concerned with the neural suppression in response to the expected inputs (Friston, 2005). As distraction is a multi-faceted construct (see Section 1.1.3 and 6.2), the neural suppression corresponding to the distractor-related processing can mean the suppression at one or more than one of the components of distraction. One possibility is that the neural responses reflecting the distractor encoding and the ability to filter out distractors are both diminished with predictable distractors. As the suppression of the two components would lead to an opposite effect on the degree of distraction, the ultimate direction of behavioural effect would depend on the relative suppression of the respective component. Neural suppression of distractor may not necessarily lead to psychological suppression of distractor.

Would temporal and feature-based distractor expectation have an interactive influence on the degree of distraction? In attention studies, the temporal expectation was shown to facilitate the extraction of feature-based regularity in the attended stimuli (Schwartze et al., 2011). Participants had a better change detection performance when they attended to the rhythmic stimuli that were more predictable (Foldal et al., 2022). However, there was no interaction between temporal and feature-based regularity on the neural responses to frequency deviant when participants were instructed to ignore the stimuli (Schwartze et al., 2011, 2013). For the task-irrelevant distractors, the temporal and feature-based expectation may also not interact in their potency to interfere with task performance.

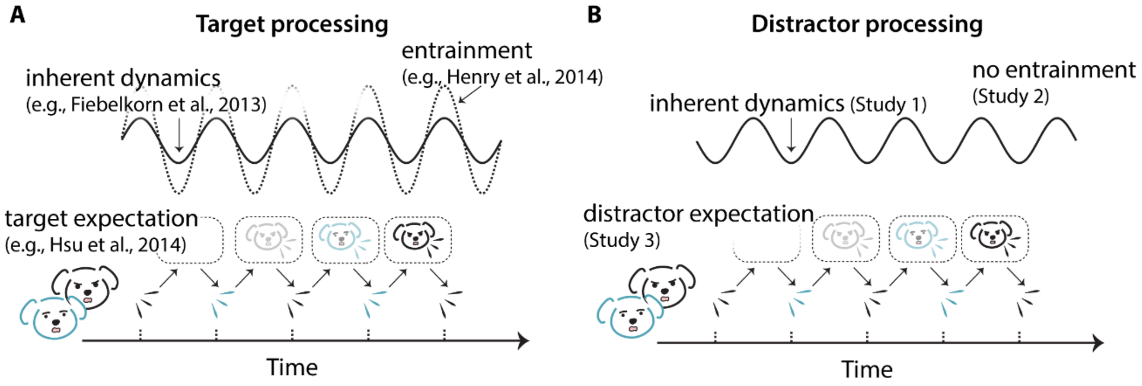

Figure 6.1. Illustration of the temporal dynamics of (A) target processing, which were examined in previous studies, and (B) distractor processing, which were examined in the 3 empirical studies in this thesis.

6.4. The primacy of behavioural evidence in the study of distraction

Throughout this thesis, behavioural evidence plays an unequivocal role in the understanding of distraction. In Studies 1 and 3, we studied the brain and behavioural dynamics by relating the behavioural evidence with neural evidence. In Study 2, we only conducted behavioural experiments in an attempt to elucidate whether distraction can be entrained by exogenous rhythms. In this section, I will argue for the primacy of behavioural evidence in the study of distraction due to the task-irrelevant and multi-faceted nature of distraction.

In opposition to the previously prevalent view that all psychological phenomena can be reduced to neurobiology (Bickle, 2003; Nagel, 1961), more and more researchers recognised the insufficiency of understanding cognition with neuroscientific evidence alone (Grasso et al., 2021; Krakauer et al., 2017; Marshall, 2009). The basic tenet of such an argument is that with neuroscientific evidence, we only acquire knowledge of cognition at the lower level of implementation (Marr, 1982). Understanding the neural implementation does not necessitate the understanding of the higher algorithmic level, which constitutes the trajectory of the cognitive process. Metaphorically, understanding all the components of a chessboard does not necessitate an understanding of how to play chess. Similarly, understanding all the biological components does not guarantee the mapping of the behavioural trajectory of an organism (Krakauer et al., 2017).

Distractors are task-irrelevant by definition. What distinguishes a task-irrelevant distractor from other task-irrelevant events is that a distractor interferes with task performance. Modulation of behavioural detriments by distraction is thus recommended to make sure that the human brain is engaged in distractor processing (Wöstmann et al., 2022). One can also argue that a lack of behavioural detriment by distraction can be attributed to the successful suppression of a distractor. However, with an absence of evidence, the hypothesis of successful distractor suppression cannot be delineated from the hypothesis that the intended distractor did not possess the potency to distract. The distractors used in Study 1 and Study 2 were shown to be distracting by comparing the behavioural performance with or without a distractor. In Study 3, rather than showing a behavioural detriment with distraction, an interactive effect was found in the behavioural performance by distractor type and with different task difficulties.

A well-designed behavioural experiment enables us to investigate the trajectory of the cognitive process, thereby laying down a theoretical foundation for the underlying neural mechanism (Buschman & Kastner, 2015). A lack of such a theoretical foundation would render the neural evidence hard to interpret. In the study of distraction, the delineation between different cognitive components of distraction is a prerequisite to shed light on the neural implementation of these components (Wöstmann et al., 2022). For example, we were able to isolate the distractibility dynamics in Study 1 by 1) ensuring that the distractor could not be expected in both its occurrence and its temporal occurrence, and 2) relating pre-distractor brain dynamics with the behavioural dynamics of distraction. On the contrary, we could not find a modulatory effect of temporal regularity on the behavioural level in Study 2. In the absence of a behavioural effect, additional neural results would not be needed as there is no cognitive phenomenon to be explained.

6.5. The methodological considerations in studying the rhythms of cognition

Although neural oscillations have been studied for decades (Bishop, 1932; Doelling & Assaneo, 2021), the separation between periodic oscillations from aperiodic neural activities has gained much attention in recent years (Donoghue et al., 2020; He, 2014). On a frequency spectrum, the periodic and aperiodic neural activities are manifested as the band-limited peak power at specific frequencies and the background power spectrum exhibiting a 1/f slope, respectively. Periodic and aperiodic oscillations are suggested to both have physiological significance. Periodic oscillations have been suggested to reflect the coordination of neural ensembles (X.-J. Wang, 2010); aperiodic oscillations and the excitation/inhibition balance in the brain are correlated (Gao et al., 2017). With distinctive physiological origins, researchers have proposed ways to isolate periodic activities from aperiodic signals to ascertain the investigation of periodic components (e.g., Donoghue et al., 2020; Wen & Liu, 2016).

In a similar vein, in the current literature on the endogenous rhythm of cognition, whether the dynamics found in behavioural measures of cognition are periodic is under debate (Brookshire, 2022; Re et al., 2022; Wöstmann, 2022). The major opposing argument states that instead of testing the periodicity of the behavioural time course, the shuffling-in-time method used in rhythmic cognition research tests the presence of a temporal structure against its absence (Brookshire, 2022). By shuffling the data in time, the aperiodic temporal structure along with the periodic temporal structure is destroyed. Hence, when comparing the original frequency spectrum versus the frequency spectrum generated from the shuffled data, one is testing against the baseline condition without a temporal structure. As a result, the existing method does not delineate the periodic temporal structure from the aperiodic temporal structure in a time series signal. While Brookshire (2022) rightfully points out the methodological consideration in studying rhythmic cognition, it does not entirely invalidate the notion that cognition is rhythmic. The critical evidence in rhythmic cognition lies within the relationship between neural and behavioural dynamics.

Studies of rhythmic cognition are usually limited in their trial count, rendering the behavioural time course less reliable (Fiebelkorn, 2022). In a typical behavioural experiment studying rhythmic cognition, the stimulus onset time should be densely sampled in order to capture a temporal profile of behavioural performance with a temporal resolution sufficient for spectral analysis (Kienitz et al., 2022). With a higher number of stimulus onset times, the experiment would be substantially longer if a higher trial number is aimed for, which is often impractical. Similarly, increasing the maximum stimulus onset interval would also inevitably lengthen the experiment time. As a result, a compromise among the length of the time course, temporal resolution, and trial numbers is needed, leading to a relatively low signal-to-noise ratio in the behavioural measure (Fiebelkorn, 2022).

The study of the brain-behaviour relationship can mitigate the problem of a low signal-to-noise ratio on the behavioural level and provide a key understanding of rhythmic cognition. The search for behavioural dynamics of cognition is based on the notion that the phase of neural oscillations signifies different states of perceptual or attentional sampling (Fiebelkorn & Kastner, 2019; VanRullen, 2016). The phase and amplitude of neural oscillations are measured over a long snippet of neural data, which provides a reliable neural measure on a single-trial level. Then, the neural phase can be used to predict the variability in behaviour. Compared with behavioural evidence alone, the relationship between neural phase and behavioural fluctuations would be stronger evidence for rhythmic cognition (Fiebelkorn, 2022; Wöstmann, 2022). The phasic relationship between slow neural oscillations and behavioural fluctuations has been demonstrated in attention (Busch et al., 2009; Helfrich et al., 2018; Landau et al., 2015) and in working memory (Siegel et al., 2009; ter Wal et al., 2021) research, in favour of the notion that cognition is rhythmic.

To answer whether the dynamics in cognition are periodic, Brookshire proposed two possible solutions (Brookshire, 2022). However, the two analysis methods are not without their caveats. For instance, the autoregressive method generates a surrogate frequency spectrum that comprises clear peaks for each permutation; the 1/f aperiodic shape of the frequency spectrum is only manifest on the averaged permuted frequency spectrum (Re et al., 2022). On the other hand, the robust estimation method has a low true-positive rate (Brookshire, 2022). To delineate periodic from aperiodic cognitive dynamics, Re et al. (2022) proposed the parameterisation of the frequency spectrum of the behavioural time course (e.g., Helfrich et al., 2018), which is methodologically similar to the study of periodic neural dynamics (Donoghue et al., 2020; Wen & Liu, 2016). A proper analysis method to extract the periodicity in behavioural dynamics of cognition would advance our understanding of rhythmic cognition.

6.6. Limitations

There are a few limitations in the present thesis. First, the present thesis did not answer whether the temporal mechanisms of distraction are independent of attention. With the focus on the temporal trajectory of distraction, we did not manipulate the corresponding temporal properties in the attended stimuli. For instance, the target stimuli in Study 1 were pure tone pips without rhythmicity; Study 2 used either temporally regular target numbers (Experiments 1 to 3) or a visual target array without rhythmicity (Experiment 4). Research has suggested that distractor-related processing can be independent of target-related processing (Gundlach et al., 2022; Schneider et al., 2018; Wöstmann et al., 2019). However, in this thesis, we cannot eliminate the possibility that the distractibility dynamics are tethered to the dynamics in attention in Study 1. In Study 3, while we demonstrated that distractor expectation influences the behavioural and neural responses of the target/distractor pair, we cannot tell if the influence is from changes directly in distractor processing, indirectly in target processing, or both. To test the independence of the temporal mechanism of distraction from attention, additional experimental manipulations should be included. For instance, in Study 1, the stimulus onset interval of the second target can be varied to capture the attentional dynamics and its interaction with the distractibility dynamics. In Study 3, we can test the influence of distractor predictability on alpha lateralisation when distractors are presented on the side and targets are presented on the front (similar to the setup used in Wöstmann et al., 2019). This way, we can confidently attribute any modulation of alpha lateralisation by distractor predictability to distractor filtering.

Second, the importance to have a clear taxonomy regarding the different components of distraction is acknowledged in this thesis. Nevertheless, not all components could be separately studied in the 3 empirical studies. For instance, in all 3 empirical studies, we could not disentangle between active versus automatic distractor suppression without a "neutral" stimulus with which the independent decrease in the response to distractor can be teased apart from pure target selection (Schneider et al., 2021; Wöstmann et al., 2022). By experimental design and pre-distractor neural measure, we were able to isolate distractibility in Study 1. In Study 3, however, we could only rely on reverse inference to speculate the role of proactive versus reactive suppression with the help of neural results (see Section 6.2). Reverse inference by neural evidence should be taken with caution as it commits a logical fallacy of affirming the consequent (Poldrack, 2006); further studies testing the hypothesis based on such inference are needed to test the individual components. Having a clear definition of each component helps to avoid erroneous reverse inference and design future experiments tailored to the components pertaining to distraction.

Research in oscillatory behavioural dynamics such as rhythmic cognition and entrainment often faces an empirical question: What is the optimal frequency underlying the dynamic behaviour? It is possible that the frequencies in the temporally regular distractors in Study 2 (1.33 Hz in Experiment 3 and 4; 4 Hz in Experiment 1 and 2) mismatched from the eigenfrequency of distractibility, which was found to oscillate in 3 – 5 Hz in Study 1. Neural networks may exhibit a frequency-specific pattern in response to an input (i.e., eigenfrequency in Helfrich et al., 2019). The exact frequency may be different depending on different factors such as the task requirement (Watrous et al., 2013) or the modality (Zoefel & VanRullen, 2017). The empirical question is to which frequency is the neural network the most sensitive. The ideal way to answer such a question is to include a wide range of frequencies and extract the frequency with the peak response. In the study of rhythmic cognition, this can be achieved by increasing the temporal resolution when sampling the stimulus onset time. In the study of entrainment, one can include a few more conditions where the exogenous rhythmic events oscillate in different frequencies. In practice, however, these methods drastically increase the experimental time and are often not feasible.

Of note, the effect sizes for the temporal dynamics of cognition seem to be small, with studies failing to report temporal fluctuations in attention (van der Werf et al., 2022), the effect of temporal regularity (Bauer et al., 2015; Lin et al., 2021), or distractor expectation with trial-by-trial predictability (Bogaerts et al., 2022). The effect size for distractor suppression was shown to be smaller than target selection (Wöstmann et al., 2019). Similarly, the effect sizes across the empirical studies in this thesis are also of small to medium size. For instance, the comparison of spectral magnitude between the co-fluctuations (i.e., cross-correlation) in distractor-present versus absent trials in Study 1 has a Cohen's d of 0.66, suggesting that the co-fluctuations of distraction are of medium effect size (J. Cohen, 1988). Similar or smaller effect sizes are found in Studies 2 and 3 (Temporal regularity effect on speed in Study 2: d = 0.23; Distractor predictability effect on alpha lateralisation: d = 0.41). Future studies should take the effect sizes into consideration to ensure sufficient statistical power in studying the temporal dynamics of distraction.

6.7. Translational implications

The investigation of the temporal dynamics of distraction in the present thesis has potential translational importance in understanding the psychopathology and pathophysiology of psychiatric disorders.

Impairments in cognitive operations are suggested to be an essential component, or even the underlying mechanism, of psychiatric disorders (Etkin et al., 2013; Morozova et al., 2022). The investigation of aberrant cognition in clinical populations may provide more information on the psychopathology of psychiatric disorders, thereby providing insights into potential intervention or treatment methods. In the study of rhythmic attention, researchers have recently started putting their focus on the abnormality of the attentional rhythms in the clinical population and found that the endogenous rhythm of attention is retained for individuals with schizophrenia (Reavis et al., 2022). On the other hand, aberrant predictive processes have been theorised to underlie the pathologies of a few psychiatric disorders (Friston et al., 2014), such as obsessive-compulsive disorder (Fradkin et al., 2020), autism (Van de Cruys et al., 2014), and schizophrenia (Sterzer et al., 2018, 2019).

Attention-deficit hyperactivity disorder (ADHD), a developmental disorder that is characterised by inattention and/or hyperactivity and impulsivity (DSM-V), has been associated with impairments in various cognitive operations such as executive function and response inhibition (J. Posner et al., 2020). Increased distractibility is one of the prominent features of ADHD (Fassbender et al., 2009; Friedman-Hill et al., 2010; Gumenyuk et al., 2005). The cognitive deficits in interference suppression in the ADHD population were accompanied by deficits in the activation of brain regions such as the left inferior frontal cortex and insula (Vaidya et al., 2005). The ADHD population also showed hyperactivation in the left insula cortex in the face of negative emotional stimuli (Vetter et al., 2018). In Study 1, we have traced the origin of distractibility dynamics to the left inferior frontal and insula cortical regions (see Chapter 3). It is conceivable that the ADHD population would exhibit an aberrant distractibility rhythm which is associated with the atypical activation pattern in the related brain regions.

Another clinical population that showed impairment in the proneness to distraction is individuals with schizophrenia (Bergman et al., 1995; Oltmanns et al., 1978). The positive symptoms of schizophrenia such as hallucination (Horga et al., 2014) and delusion (Schmack et al., 2015) have been associated with deficient predictive processes (Sterzer et al., 2018). While the negative symptoms such as cognitive deficits and blunted emotional expression are suggested to be more detrimental in the long run (McCutcheon et al., 2020), its psychopathology in the framework of the predictive process is less well-studied (Jeganathan & Breakspear, 2021). Reduction in the pre-attentive mismatch response (i.e., mismatch negativity; MMN) was found in the schizophrenia population compared to healthy control (Kirihara et al., 2020; Wacongne, 2016), suggesting that the deficits in the predictive process are already evident outside the centre of attention. Whether and how the deficient predictive process may influence negative symptoms such as distractibility remains unknown. Understanding how the aberrant predictive process in the task-irrelevant domain modulates the proneness to distraction may help to arrive at a more comprehensive understanding of the negative symptoms of schizophrenia.

7. Conclusion

The three behavioural and electrophysiological studies in this thesis collectively elucidate the many facets of how distraction unfolds in time. Throughout this thesis, distraction is shown to (1) exhibit endogenous dynamics, (2) not entrained by exogenous rhythms, and (3) be influenced by distractor expectation formed by local statistics. The empirical results of this thesis urge for a theoretical reformulation of different aspects of auditory distraction.

First, the endogenous proneness to distraction fluctuates with a rate of approximately 3 – 5 cycles per second. The temporal fluctuations are demonstrated by the co-fluctuations of the behavioural and neural measures of distraction by distractor onset time. The distractibility dynamics were found to originate from the left inferior frontal cortex and insula cortex, which may serve as a nexus for the orchestration between the maintenance of goal-related memory representation and interference from the potential external distraction. The discovery of the endogenous dynamics in distractibility urges a theoretical reformulation of the spotlight theory of attention by acknowledging the existence of dynamic cognition outside the spotlight of attention.

Second, the proneness to distraction is not entrained by exogenous rhythmic events. The temporal regularity of distractors did not have a direct impact on the precision of memory representation (i.e., primary performance metric), but rather indirectly on response behaviour such as speed and metacognition (i.e., secondary performance metric). The results suggest that although distractibility may follow an endogenous rhythm, it is not influenced by exogenous rhythms. However, the exogenous rhythms embedded in a distracting sequence may not go unnoticed. Rather, they may play an indirect role by influencing motor preparation or the response bias during a working memory task. The null results in the primary performance metric and significant results in the secondary performance metrics demonstrate the necessity to incorporate cognitive operations such as metacognition into the theorisation of auditory distraction.

Third, distractor expectation can be formed by the local transition probability in the distracting sequence even without the influence of global statistics. Furthermore, the influence of distractor expectation on the ultimate degree of distraction depends on the perceptual and cognitive load of the task. Electrophysiological results showed that distractor expectation and cognitive load interactively influenced the neural correlates of attentional selection. Distractor expectation also reduced the reactive filtering of the distractor. While the neurophysiological evidence largely converges with the prevalent expectation suppression account under the predictive processing framework, which states that distractor expectation reduces the response to a distractor, behavioural evidence showed mixed results in the direction in which distractor expectation influences the potency to distract. In future studies, the delineation between neural and psychological suppression should be carefully examined when considering the modulatory influence of distractor expectation.

All in all, distraction is a dynamic construct whose temporal mechanism has long been neglected. Elucidating how the ignored side of the attentional filter unfolds in time, we can better understand how to situate ourselves in a complex world full of distractions.

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A

ADHD	attention-deficit hyperactivity disorder
ALI	alpha lateralisation index
AMI	attentional modulation index
ANOVA	analysis of variance

B

BF	Bayes factor

C

CNV	contingent negative variation

E

EEG	electroencephalography
ERP	event-related potential

F

FFT	fast Fourier transform
fNIRS	functional near-infrared spectroscopy

I

ICA	independent component analysis
ITPC	inter-trial phase coherence

L

LCMV	linearly-constrained minimum variance
LORETA	low resolution electromagnetic tomography

M

MMN	mismatch negativity
MRI	magnetic resonance imaging

P

P_D	distractor positivity

R

RT	response time

S

SFN	sustained frontal negativity
SPL	sound pressure level
SNR	signal-to-noise ratio
SOA	stimulus onset asynchrony

Summary

Introduction

The environment abounds with sensory information. Selective attention describes the prioritisation of task-relevant targets while ignoring the task-irrelevant distractors. As the human brain is limited in resources, selective attention is essential for successful performance in goal-directed tasks. The stage at which the distractors are filtered out has long been debated in previous research. While previous evidence supports both early (Broadbent, 1958; Treisman, 1960) and late selection (Duncan, 1980), researchers have proposed that the locus of the attentional filter depends on the perceptual and cognitive load of the current task (Lavie, 1995; 2005).

With a disproportional focus on target selection in attentional filtering research, researchers recently started to probe into the mechanisms by which task-irrelevant distractors are filtered out. The final degree of distraction mainly depends on two endogenous factors: distractibility and distractor suppression. Distractibility describes the endogenous proneness to external distraction (Forster & Lavie, 2016; Mayes & Calhoun, 2002; Wais et al., 2012). Previous studies assumed distractibility to evolve, if at all, only on a long temporal scale such as across developmental stages (K.L. Campbell et al., 2012; Kannass et al., 2006) or experimental sessions (Forster & Lavie, 2014). The temporal trajectory of distractibility on a shorter temporal scale within one second has been unclear.

Researchers have recently suggested delineating different forms of distractor suppression (Geng, 2014; Wöstmann et al., 2022). For instance, the selective inhibition of distractors can involve the reactive disengagement of distractor processing (i.e., reactive suppression; Geng, 2014) or preparatory inhibition of the anticipated distractors (i.e., proactive suppression; Geng, 2014). Furthermore, active distractor suppression independent of the target selection process should be distinguished from the collateral deselection of task-irrelevant events (i.e., automatic suppression; Schneider et al., 2021).

The overarching aim of the present thesis is to elucidate how distraction unfolds in time with a focus on endogenous brain dynamics and exogenous distractor dynamics. The human brain is ubiquitous in neural oscillations (Groppe et al., 2013; Keitel & Gross, 2016). Neural oscillations have been suggested to be instrumental to the temporal dynamics of cognitive operations (Keitel et al., 2022; Schroeder et al., 2009). The external environment is full of regular structures which are predictable in time or in terms of distractors' features. With three empirical studies, this thesis set out to elucidate how endogenous brain dynamics and exogenous distractor dynamics play a role in the unfolding of distraction.

The endogenous brain dynamics have been suggested to subserve the endogenous rhythms of cognition (VanRullen, 2016; Fiebelkorn & Kastner, 2018). The spotlight of attention, which was long assumed to be static (M. I. Posner et al., 1980), has recently been theorised to be blinking over time (VanRullen et al., 2007). The waxing and waning of attentional sampling are proposed to be concomitant with the waxing and waning in the excitability of the relevant neural networks (VanRullen, 2016; Fiebelkorn & Kastner, 2018), which led to the prediction that the neural phase in these relevant brain regions could explain the fluctuations in behavioural performance (Helfrich et al., 2018). In the study of distraction, the temporal dynamics of distractibility is largely unknown, with preliminary evidence suggesting < 4 Hz fluctuations of the behavioural and neural measures of distraction (Wöstmann et al., 2020).

Rhythms are ubiquitous in the external environment. In attention research, it has been established that the human brain makes use of external rhythms for the selection of task-relevant inputs (Large & Jones, 1999; Lakatos et al., 2019; Obleser & Kayser, 2019). When it comes to distraction, the evidence of the behavioural modulation by the temporal regularity of distractors is mixed. Studies found facilitatory (Jones & Macken, 1995; Makov & Zion Golumbic, 2020) or disruptive (Parmentier & Beaman, 2015) effect of the distractor regularity in time on the final behavioural outcome, which calls for a systematic investigation of the scope of behavioural detriment by distractors with different levels of temporal regularity.

The human brain is posited as an active agent which constantly makes predictions of the external world based on past experience (Friston, 2005; Ivry & Knight, 2002; Von Helmholtz, 1867). A rich body of literature shows that the brain is capable of extracting the statistical regularity embedded in task-irrelevant events (e.g., Naatanen & Michie, 1989; Sato et al., 2000; Mittag et al., 2016). Whether the task-irrelevant events with different levels of predictability possess different potency to distract remains unclear. Studies on the spatial expectation of distractors show converging evidence in support of the notion that predictable distractors are less distracting (i.e., expectation suppression; Noonan et al., 2018). Nevertheless, studies using local predictability, such as transition probability of distractor presence (Bogaerts et al., 2020) or semantic predictability (Wöstmann et al., 2016) did not support the expectation suppression account. The inconsistent results from these studies suggest that there may be some underlying factors that potentially modulate the influence of feature-based prediction on distractor processing.

Experiments and Results

In Study 1, we recorded EEG while participants performed a pitch discrimination task with an auditory distractor in between the two target pure tones. The distractor occurred unexpectedly both in its temporal occurrence and its occurrence. We found that behavioural sensitivity and distractor-evoked neural response co-fluctuated at a subsecond time scale with between 3 and 5 cycles per second (i.e., 3 – 5 Hz). Furthermore, the pre-distractor phase of neural oscillations in similar frequencies explained the fluctuations in behavioural sensitivity, which showed the strongest evidence in the inferior frontal and insular cortical regions. These results demonstrate that distractibility follows inherent dynamics which originate from the periodic oscillations in regions associated with cognitive control.

We turned from endogenous to exogenous dynamics of distraction in Study 2. With 4 behavioural experiments, we aimed at pushing the scope of distractor interference by distractors with different levels of temporal regularity. While the precision of memory representation (i.e., primary performance metric) was not modulated by the temporal regularity of distractors, response behaviour such as speed or response bias varied with the temporal regularity of distractors. For instance, participants were faster in memory recall and had a more conservative bias when the distractors were regular in time. The results suggest that the temporal regularity of distractors may have an impact on the often-neglected cognitive operations other than working memory, and ultimately influence the task-relevant cognitive process.

Having not found an influence of the exogenous temporal dynamics on the ultimate degree of distraction, we explored how the brain and behavioural dynamics could be modulated by expectation formed by distractor predictability on a local scale. Specifically, we investigated whether local transition probability embedded in the distractors, which are free from the influence of global statistics, would facilitate the formation of distractor expectation. Furthermore, we hypothesised that the influence of distractor expectation on the potency to distract depends on the perceptual or cognitive load of the current task. Behaviourally, distractor predictability interacted with stimulus intensity and working memory load in its influence on the working memory recognition performance. On the neural level, post-target/distractor pair alpha lateralisation was reduced with predictable distractors. Distractor predictability also influenced the pre- and post-stimulus sustained responses by interacting with the working memory load. The results are consistent with the view of neural suppression by expectation, which may give rise to the dynamical modulation of behavioural distraction.

Discussion

Our findings demonstrate that 1) distractibility follows endogenous dynamics, 2) the proneness to distraction does not depend on the exogenous rhythms embedded in distractors, and 3) the potency of a distractor to interfere with task performance is indirectly influenced by distractor expectation derived from local statistics.

Distraction is a multi-faceted construct. However, the taxonomy in the current body of literature with regard to the components of distraction has not been well defined (e.g., Geng, 2014; Schneider et al., 2021). Separating the endogenous proneness to distraction (i.e., distractibility) from the suppression of external distraction (i.e., distractor suppression), and disentangling the many forms of distractor suppression (e.g., proactive versus reactive suppression), is needed to arrive at a coherent framework of distraction (Wöstmann et al., 2022). A theoretical foundation of distraction would further our understanding of the behavioural trajectory and neural implementation of distraction.

While distraction has been suggested to operate independently from target selection, the extent to which distraction exhibits similar temporal dynamics as shown in attention research remains unknown. We demonstrate the scope of temporal dynamics in distraction by showing that distractibility exhibits endogenous dynamics but is not subject to exogenous dynamics. This highlights that rhythmic cognition is a general phenomenon tethered to the neural dynamics of the relevant neural regions; Entrainment by exogenous rhythms is an attention-specific process that may serve as an amplification of task-relevant inputs needed for successful task performance (Lakatos et al., 2019).

In the absence of evidence on the influence of temporal regularity in exogenous inputs, neural suppression by expectation still holds in terms of distractor expectation derived from local transition probability. Expectation formation is suggested to be a reiterative process where the prediction model of the upcoming distractor is updated (Friston, 2005). The modulation of post-stimulus alpha lateralisation and sustained neural activities may subserve the changes in distractor filtering and the shielding of memory representation from distraction, respectively. The cascade of neural responses associated with distractor expectation accentuates the importance to study the relative contribution of different components of distraction in the unfolding of distraction with different levels of expectation.

Zusammenfassung

Einführung

Die Umwelt ist reich an sensorischen Informationen. Selektive Aufmerksamkeit beschreibt die Priorisierung aufgabenrelevanter Ziele bei gleichzeitiger Ausblendung aufgabenirrelevanter Ablenkungen. Da die Ressourcen des menschlichen Gehirns begrenzt sind, ist die selektive Aufmerksamkeit eine wesentliche Voraussetzung für die erfolgreiche Bewältigung zielgerichteter Aufgaben. Die Phase, in der die Ablenkungen herausgefiltert wird, ist in der bisherigen Forschung lange umstritten gewesen. Während es sowohl Belege für eine frühe (Broadbent, 1958; Treisman, 1960) als auch für eine späte Selektion (Duncan, 1980) gibt, haben Forschende vorgeschlagen, dass der Ort des Aufmerksamkeitsfilters von der wahrnehmungsbezogenen und kognitiven Belastung der aktuellen Aufgabe abhängt (Lavie, 1995; 2005).

Da sich die Forschung im Bereich der Aufmerksamkeitsfilterung unverhältnismäßig stark auf die Zielselektion konzentriert, haben Forschende vor kurzem damit begonnen, die Mechanismen zu untersuchen, durch die aufgabenirrelevante Distraktoren herausgefiltert werden. Der endgültige Grad der Ablenkung hängt hauptsächlich von zwei endogenen Faktoren ab: Ablenkbarkeit und Unterdrückung von Distraktoren. Die Ablenkbarkeit beschreibt die endogene Anfälligkeit für externe Ablenkung (Forster & Lavie, 2016; Mayes & Calhoun, 2002; Wais et al., 2012). Frühere Studien gingen davon aus, dass sich Ablenkbarkeit, wenn überhaupt, nur auf einer langen zeitlichen Skala entwickelt, etwa über Entwicklungsstufen (K.L. Campbell et al., 2012; Kannass et al., 2006) oder experimentelle Sitzungen (Forster & Lavie, 2014). Der zeitliche Verlauf der Ablenkbarkeit auf einer kürzeren zeitlichen Skala mit einer Dauer von maximal einer Sekunde war bisher unklar.

Forschende haben kürzlich vorgeschlagen, verschiedene Formen der Unterdrückung von Distraktoren zu unterscheiden (Geng, 2014; Wöstmann et al., 2022). So kann die selektive Unterdrückung von Distraktoren die reaktive Unterbrechung der Verarbeitung von Distraktoren (d. h. reaktive Unterdrückung; Geng, 2014) oder die vorbereitende Unterdrückung der erwarteten Distraktoren (d. h. proaktive Unterdrückung; Geng, 2014) beinhalten. Darüber hinaus sollte die aktive, vom Zielauswahlprozess unabhängige Unterdrückung von Distraktoren von der kollateralen Deselektion aufgabenirrelevanter Ereignisse unterschieden werden (d. h. automatische Unterdrückung; Schneider et al., 2021).

Das übergeordnete Ziel der vorliegenden Arbeit ist es, zu klären, wie sich Ablenkung im Laufe der Zeit entfaltet, wobei der Schwerpunkt auf der endogenen Dynamik des Gehirns und der exogenen Dynamik der Ablenkungsfaktoren liegt. Im menschlichen Gehirn sind neuronale Oszillationen allgegenwärtig (Groppe et al., 2013; Keitel & Gross, 2016). Es wird angenommen, dass neuronale Oszillationen für die zeitliche Dynamik kognitiver Vorgänge von Bedeutung sind (Keitel et al., 2022; Schroeder et al., 2009). Die Umwelt ist voller regelmäßiger Strukturen, die zeitlich oder in Bezug auf die Eigenschaften von Distraktoren vorhersehbar sind. Mit drei empirischen Studien soll in dieser Arbeit geklärt werden, wie die endogene Dynamik des Gehirns und die exogene Dynamik der Distraktoren bei der Entfaltung der Ablenkung eine Rolle spielen.

Es wird angenommen, dass die endogene Hirndynamik den endogenen Rhythmen der Kognition untergeordnet ist (VanRullen, 2016; Fiebelkorn & Kastner, 2018). Lange Zeit wurde Aufmerksamkeit als eine Art statischer Scheinwerfer betractet (M. I. Posner et al., 1980). 2007 wurde jedoch die Theorie aufgestellt, dass er „blinkt“, die Aufmerksamkeit also nicht statisch ist, sondern oszillert (VanRullen et al., 2007). Es wird angenommen, dass das Zu- und Abnehmen der Aufmerksamkeitsabtastung mit dem Zu- und Abnehmen der Erregbarkeit der relevanten neuronalen Netzwerke einhergeht (VanRullen, 2016; Fiebelkorn & Kastner, 2018), was zu der Annahme führte, dass die neuronale Phase in diesen relevanten Hirnregionen die Schwankungen der Verhaltensleistung erklären könnte (Helfrich et al., 2018). In der Ablenkungsforschung ist die zeitliche Dynamik der Ablenkbarkeit weitgehend unbekannt, wobei vorläufige Erkenntnisse auf < 4 Hz-Fluktuationen der verhaltensbezogenen und neuronalen Maße der Ablenkung hindeuten (Wöstmann et al., 2020).

Rhythmen sind in der Umwelt allgegenwärtig. In der Aufmerksamkeitsforschung wurde festgestellt, dass das menschliche Gehirn die externen Rhythmen für die Auswahl aufgabenrelevanter Inputs nutzt (Large & Jones, 1999; Lakatos et al., 2019; Obleser & Kayser, 2019). Was die Ablenkung betrifft, so ist die Evidenz zur Verhaltensmodulation durch die zeitliche Regelmäßigkeit von Distraktoren gemischt. In Studien wurden förderliche (Jones & Macken, 1995; Makov & Zion Golumbic, 2020) oder störende (Parmentier & Beaman, 2015) Auswirkungen der zeitlichen Regelmäßigkeit von Distraktoren auf das endgültige Verhaltensergebnis festgestellt, was eine systematische Untersuchung des Ausmaßes der Beeinträchtigung des Verhaltens durch Distraktor mit unterschiedlicher zeitlicher Regelmäßigkeit erfordert.

Das menschliche Gehirn wird als aktiver Akteur angesehen, der auf der Grundlage früherer Erfahrungen ständig Vorhersagen über die Außenwelt trifft (Friston, 2005; Ivry & Knight, 2002; Von Helmholtz, 1867). Eine umfangreiche Literatur zeigt, dass das Gehirn in der Lage ist, statistische Regelmäßigkeiten zu extrahieren, die in aufgabenirrelevante Ereignisse eingebettet sind (z. B. Naatanen & Michie, 1989; Sato et al., 2000; Mittag et al., 2016). Ob die aufgabenirrelevanten Ereignisse mit unterschiedlichem Grad an Vorhersagbarkeit eine unterschiedliche Ablenkungswirkung haben, bleibt jedoch unklar. Studien zur räumlichen Erwartung von Distraktoren zeigen konvergierende Belege für die Annahme, dass vorhersehbare Ablenker weniger ablenkend sind (d. h. Erwartungsunterdrückung; Noonan et al., 2018). Studien mit lokaler Vorhersagbarkeit, wie z. B. der Übergangswahrscheinlichkeit des Vorhandenseins von Distraktoren (Bogaerts et al., 2020) oder semantischer Vorhersagbarkeit (Wöstmann et al., 2016), unterstützten jedoch nicht den Ansatz der Erwartungsunterdrückung. Die widersprüchlichen Ergebnisse dieser Studien deuten darauf hin, dass es einige zugrundeliegende Faktoren geben könnte, die den Einfluss der merkmalsbasierten Vorhersage auf die Verarbeitung von Distraktoren modulieren könnten.

Experimente und Ergebnisse

In Studie 1 wurde die neuronale Aktivität mittels EEG erhoben, während die Teilnehmer*innen eine Tonhöhenunterscheidungsaufgabe mit einem auditiven Distraktor zwischen den beiden Ziel-Reintönen durchführten. Der Distraktor trat sowohl in seinem zeitlichen Auftreten als auch in seinem Auftreten unerwartet auf. Wir fanden heraus, dass die behaviorale Sensitivität und die durch den Distraktor hervorgerufene neuronale Reaktion auf einer Zeitskala im Millisekundenbereich mit 3 bis 5 Zyklen pro Sekunde (d. h. 3 - 5 Hz) gemeinsam schwankten. Darüber hinaus erklärte die Prä-Distraktor-Phase neuronaler Oszillationen mit ähnlichen Frequenzen die Fluktuationen der Verhaltensempfindlichkeit, die sich am stärksten in den inferioren frontalen und insularen kortikalen Regionen zeigte. Diese Ergebnisse zeigen, dass die Ablenkbarkeit einer inhärenten Dynamik folgt, die ihren Ursprung in den periodischen Oszillationen in Regionen hat, die mit der kognitiven Kontrolle verbunden sind.

In Studie 2 wandten wir uns von der endogenen zur exogenen Dynamik der Ablenkbarkeit. Mit 4 Verhaltensexperimenten wollten wir den Umfang der Ablenkungsinterferenz durch Distraktoren mit unterschiedlicher zeitlicher Regelmäßigkeit ausweiten. Während die Präzision der Gedächtnisrepräsentation (d. h. die primäre Leistungsmetrik) nicht durch die zeitliche Regelmäßigkeit der Distraktoren moduliert wurde, variierte das Antwortverhalten wie Geschwindigkeit oder Antwortverzerrung mit der zeitlichen Regelmäßigkeit der Distraktoren. So waren die Teilnehmer*innen beispielsweise schneller im Gedächtnisabruf und hatten eine konservativere Tendenz, wenn die Distraktoren zeitlich regelmäßig waren. Die Ergebnisse deuten darauf hin, dass die zeitliche Regelmäßigkeit der Ablenkungen einen Einfluss auf die oft vernachlässigten kognitiven Operationen außerhalb des Arbeitsgedächtnisses haben und letztlich den aufgabenrelevanten kognitiven Prozess beeinflussen kann.

Nachdem wir keinen Einfluss der exogenen zeitlichen Dynamik auf den finalen Grad der Ablenkung gefunden hatten, untersuchten wir, wie die Gehirn- und Verhaltensdynamik durch die Erwartung moduliert werden könnte, die durch die Vorhersagbarkeit der Distraktoren auf lokaler Ebene entsteht. Insbesondere untersuchten wir, ob die in den Distraktoren eingebettete lokale Übergangswahrscheinlichkeit, die frei vom Einfluss globaler Statistiken ist, die Bildung der Distraktor-Erwartung erleichtern würde. Außerdem stellten wir die Hypothese auf, dass der Einfluss der Ablenkungserwartung auf die Ablenkungsfähigkeit von der perzeptuellen oder kognitiven Belastung der aktuellen Aufgabe abhängt. Auf der Verhaltensebene beeinflusste die Vorhersagbarkeit des Distraktor in Wechselwirkung mit der Stimulusintensität und der Belastung des Arbeitsgedächtnisses die Erkennungsleistung im Arbeitsgedächtnis. Auf neuronaler Ebene war die Alpha-Lateralisierung des Paares Post-Target/Distraktor bei vorhersehbaren Distraktoren reduziert. Die Vorhersagbarkeit des Distraktors beeinflusste auch die anhaltenden Reaktionen vor und nach dem Stimulus, indem sie mit der Belastung des Arbeitsgedächtnisses interagierte. Die Ergebnisse stimmen mit der Auffassung überein, dass die neuronale Unterdrückung durch Erwartung zu einer dynamischen Modulation der Verhaltensablenkung führen kann.

Diskussion

Unsere Ergebnisse zeigen, dass 1) die Ablenkbarkeit einer endogenen Dynamik folgt, 2) die Neigung zur Ablenkung nicht von exogenen Rhythmen abhängt, die in Distraktoren eingebettet sind, und 3) die Stärke eines Distraktors, die Aufgabenerfüllung zu beeinträchtigen, indirekt von der aus lokalen Statistiken abgeleiteten Distraktor-Erwartung beeinflusst wird.

Ablenkung ist ein vielschichtiges Konstrukt. Allerdings ist die Taxonomie in der aktuellen Literatur in Bezug auf die Komponenten der Ablenkung nicht gut definiert (z. B. Geng, 2014; Schneider et al., 2021). Die Trennung der endogenen Neigung zur Ablenkung (d.

h. Ablenkbarkeit) von der Unterdrückung externer Ablenkung (d. h. Unterdrückung von Distraktoren) und die Entflechtung der vielen Formen der Unterdrückung von Distraktoren (z. B. proaktive versus reaktive Unterdrückung) sind notwendig, um zu einem kohärenten Rahmen der Ablenkung zu gelangen (Wöstmann et al., 2022). Eine theoretische Grundlage der Ablenkung würde unser Verständnis des Verhaltensverlaufs und der neuronalen Umsetzung der Ablenkung fördern. Obwohl angenommen wurde, dass Ablenkung unabhängig von der Auswahl des Zielreizes funktioniert, ist nicht bekannt, inwieweit Ablenkung eine ähnliche zeitliche Dynamik aufweist wie in der Aufmerksamkeitsforschung gezeigt. Wir demonstrieren den Umfang der zeitlichen Dynamik bei Ablenkung, indem wir zeigen, dass Ablenkbarkeit eine endogene Dynamik aufweist, aber keiner exogenen Dynamik unterworfen ist. Dies unterstreicht, dass rhythmische Kognition ein allgemeines Phänomen ist, das mit der neuronalen Dynamik der relevanten neuronalen Regionen zusammenhängt; die Anziehung durch exogene Rhythmen ist ein aufmerksamkeitsspezifischer Prozess, der als Verstärkung von aufgabenrelevanten Inputs dienen kann, die für eine erfolgreiche Aufgabenerfüllung erforderlich sind (Lakatos et al., 2019).

In Ermangelung von Beweisen für den Einfluss der zeitlichen Regelmäßigkeit exogener Inputs gilt die neuronale Unterdrückung durch Erwartung immer noch in Bezug auf die aus der lokalen Übergangswahrscheinlichkeit abgeleitete Erwartung eines Distraktors. Es wird angenommen, dass die Erwartungsbildung ein sich wiederholender Prozess ist, bei dem das Vorhersagemodell des kommenden Distraktors aktualisiert wird (Friston, 2005). Die Modulation der Post-Stimulus-Alpha-Lateralisierung und die anhaltenden neuronalen Aktivitäten könnten den Veränderungen bei der Filterung von Distraktoren bzw. der Abschirmung der Gedächtnisrepräsentation vor Ablenkung dienen. Die Kaskade neuronaler Reaktionen, die mit der Erwartung eines Distraktors einhergeht, macht deutlich, wie wichtig es ist, den relativen Beitrag verschiedener Komponenten der Ablenkung bei der Entfaltung der Ablenkung mit unterschiedlichen Erwartungsniveaus zu untersuchen.