Predicting What and When: How Feature-Temporal Regularities Influence Dynamic Visual Search



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Abstract

From spotting a friend in a crowd to locating information on a busy screen, finding important target items amidst distraction is a common yet demanding everyday task. Although visual search has typically been studied in static contexts, real-world environments are dynamic, evolving continuously as we search. Predictions about *what* features a target will have are known to facilitate search, yet it remains unclear whether these biases can flexibly shift between features at moments *when* they are known to be the most relevant. This flexibility would enable search to remain efficient as task-relevant features change over time. I address this gap using novel dynamic visual search tasks that contain feature-temporal regularities — predictable associations between stimulus timing and non-spatial features. *Chapter 2* investigates whether learning predictable associations between target timing, features, and responses can adaptively modulate performance, feature-based attentional capture, and motor preparation. *Chapter 3* extends this by testing whether feature-temporal predictions can facilitate visual search independently of response predictability. *Chapter 4* asks whether feature-temporal regularities can be exploited when they concern distractors rather than targets. Together, these studies highlight how search can evolve over time. Importantly, these processes can be systematically biased by feature-temporal regularities, with temporally-contingent predictions modulating both perceptual and motor mechanisms as well as the handling of both targets and distractors. Methodologically, this thesis contributes novel dynamic tasks and continuous measures for tracking search as it unfolds, while also highlighting the challenges of studying temporal expectations in extended contexts. More broadly, this work provides insight into how humans can flexibly extract and exploit temporal regularities over time to guide behaviour in complex dynamic environments.

Statement of Contribution

The work presented in this thesis has benefitted greatly from the guidance of my DPhil supervisors, Sage Boettcher and Kia Nobre. The task designs and analysis approaches described in each experimental chapter were developed in collaboration with my supervisory team. I collected the data and led the analysis for all experiments included in this thesis. The work presented in Chapter 2 Experiment 2 has been posted as a preprint on the server bioRxiv and can be found here: https://doi.org/10.1101/2025.04.18.649503. I have the co-authors' permission to include parts of that text in the present thesis. The writing of this thesis is my own and was conducted under the supervision of Sage Boettcher and Kia Nobre.

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1 General Introduction

1.1 General Overview

Visual search is a fundamental and frequent everyday behaviour that allows us to locate goal-relevant target items in cluttered environments, often guiding subsequent actions. Consider entering a busy workplace canteen at lunchtime and, as you do every day, searching for either of your two friends to sit next to. In such an environment, locating and sitting with your friends (the 'targets') while ignoring other people and objects ('distractors') is a cognitively demanding task that requires coordination across perception, attention, and motor processes. Despite this, visual search in real-world settings is often made more manageable by the cognitive system using environmental regularities to help prioritise processing of relevant information. Prioritisation can guide search across space on the basis of regularities relating to *where* to look (e.g., the table where your friends like to sit) or *what* to look at (e.g., people with your friends' usual hairstyles). But, like many real-world environments, the canteen is highly dynamic, with different people entering and exiting across time. Accordingly, real-world search is rarely only a matter of where or what to look at, but also *when*.

Fortunately, just as the *where* and *what* of the world are often structured, so too is the *when*. Everyday environments are filled with predictable temporal intervals between sensory events. Extracting these regularities allows us to form temporal expectations about when relevant events will occur and prepare accordingly, such as predicting when a traffic light will change or a kettle will boil (for a recent review, see Seibold et al., 2023). Importantly, different types of target items defined by different features can also differ consistently in their temporal properties. For example, buses (supposedly) arrive at regular intervals, whereas taxis pass by more irregularly and thus require more constant monitoring. In returning to the canteen, your past experience might tell you that one friend

(e.g., with blonde hair) typically arrives around the same time as you, while the other (e.g., with brunette hair) tends to arrive later. In this case, it would be adaptive to *temporally tune* your feature-based processing: first limiting your search to blondes, before later prioritising brunettes. This illustrates what I refer to as *feature-temporal* regularities, in which the timing of items is predictably linked to their non-spatial features.

Despite their intuitive utility, feature-temporal regularities have not been systematically examined within the context of multi-target visual search. Much of the visual search literature has relied on static displays, allowing researchers to isolate spatial and feature-based influences from the temporal structures that characterise real-world environments. Increasingly, researchers have begun adopting more *dynamic visual search* (DVS) tasks, but investigations of temporal expectations within these contexts remain limited. A handful of very recent visual search studies have explored the effects of spatiotemporal regularities – relating to *where* and when relevant items are likely to appear – though no equivalent investigations have been conducted for feature-temporal regularities. The present thesis aims to address this gap.

The empirical work in this thesis aims to investigate whether, and how, feature-temporal regularities adaptively influence visual search in dynamic environments. First, I examine whether target-related feature-temporal regularities can tune visual search behaviour (Chapter 2), both alongside and independently of temporal regularities in motor responses (Chapter 3). Next, I examine whether regularity-based predictions can mitigate the impact of feature-temporally predictable distraction, limiting performance-impairing engagement with non-relevant items (Chapter 4). This would be akin to learning that certain people you wish to avoid also arrive at predictable times, allowing you to potentially down-weight their influence on your task of finding your friends. Methodologically, this thesis employs newly developed DVS tasks, complemented by an integration

of eye tracking, electromyography (EMG), and continuous behavioural probes to reveal temporally tuned shifts in underlying processes.

Prior to these empirical chapters, this introductory chapter reviews relevant theoretical and methodological literature, highlighting both key insights and constraints. I begin with an overview of existing work on visual search and temporal expectations, before considering the small body of research that has attempted to combine the two. Here, I advance the view that both the cognitive processes that underlie visual search, as well as the real-world environments in which search occurs, are rarely static. These dynamics highlight the need to explore how temporal regularities in our surroundings may be learned and used to modulate search behaviour systematically over time. This chapter concludes by outlining the specific aims of this thesis.

1.2 Visual Search

Visual search is a prevalent behaviour in everyday life, as we continuously shift between locating goal-relevant items and acting upon them: from finding a friend at lunch, to locating a button on a web interface, or searching for our keys when heading home. Its efficiency is all the more striking given the inherent limitations in the human visual system, including restricted visual acuity in the periphery, bottlenecks in visual attention, and capacity limits in visual working memory (Carrasco et al., 1995; Luck & Vogel, 1997; Wolfe, 2021). Understanding how search behaviour adapts to these constraints is essential for explaining how humans successfully perform everyday tasks. Simple and controlled static visual search tasks have long been a popular and valuable laboratory method for investigating fundamental cognitive mechanisms (Chan & Hayward, 2013; Treisman & Gelade, 1980; Wolfe, 2020). While such tasks have yielded foundational insights, they both simplify the challenges of real-world search and mask the efficiency that characterises it, i.e., our ability to quickly find targets

in cluttered environments. Overall, advancing the study of visual search carries important implications at applied, theoretical, and methodological levels.

In everyday life outside of the laboratory, targets rarely appear in isolation. Instead, they are embedded among many irrelevant items that compete for selection. Because the human visual system cannot process and recognise all items in a busy scene simultaneously (Carrasco, 2011; Lennie, 2003; Schneider & Shiffrin, 1977), attention must first select individual items for further processing (Treisman & Gelade, 1980; Wolfe, 2021). To serially attend to every element of a scene is slow and effortful. Fortunately, this is rarely required for successful search. Instead, targets can be located efficiently by adaptively guiding selective attention according to systematic influences, rather than at random (Broadbent, 1958; Carrasco, 2011; Nobre, 2018; Võ et al., 2019; Wolfe, 2021). A central question in visual search research, then, is: what kinds of information can be used to guide attention efficiently?

By manipulating the contents of search displays, lab-based experiments have revealed many kinds of stimulus attributes that can serve as a basis for attentional guidance. These include spatial location, size, and non-spatial features such as colour (Wolfe, 2020; Wolfe & Horowitz, 2017). Research has also revealed several distinct sources of attentional guidance. Traditionally, distinctions have been drawn between two key sources: *bottom-up* and *top-down*.

Bottom-up, or stimulus-driven, attention automatically prioritises stimuli that differ substantially from their surroundings rendering them highly salient, such as a person wearing a bright red coat in a crowd of grey coats (Wolfe & Horowitz, 2017). Salient targets can be identified rapidly and with little effort, while attentional capture by salient distractors can delay target identification (Theeuwes, 1992).

In contrast, top-down, or goal-driven, attention involves the voluntary prioritisation of stimuli relevant to an observer's current goals or expectations (Corbetta & Shulman, 2002; Posner, 1980).

For instance, guiding your attention toward people with what you know to be your friend's hair colour will help you to find them faster. These goal-driven biases are thought to rely on attentional templates, internal representations of target-defining properties (Carlisle et al., 2011; Desimone & Duncan, 1995; Duncan & Humphreys, 1989; Wolfe, 2021). In the laboratory, attentional templates are often based on knowledge derived from explicit symbolic cues about a target, such as a coloured fixation cross indicating its colour, or an arrow pointing to its likely location. That said, attentional templates are also flexible and adaptive, often containing non-veridical representations of target attributes that are more effective for guiding search given specific task demands (Boettcher & Nobre, 2025; Lerebourg et al., 2023; Witkowski & Geng, 2019; X. Yu et al., 2023). Internal representations of distractor properties, known as negative templates, may also guide attention away from irrelevant items, though their existence and utility remain debated (Carlisle, 2023).

Beyond this historically-recognised dichotomy, a third source of attentional guidance has more recently gained widespread acceptance: *selection history*. Selection history refers to attentional biases shaped by prior experience, regardless of task goals or physical salience (Awh et al., 2012; Liesefeld et al., 2024). Such guidance often arises from visual statistical learning of environmental regularities across searches (Theeuwes, 2019), but may also reflect the lingering influence of past rewards or expectations about the typical structure of our surroundings, known as *scene grammar* (B. A. Anderson et al., 2021; Failing & Theeuwes, 2018; Võ et al., 2019; Wolfe, 2021). Predictions based on learnt regularities have been shown to guide attention towards high-probability target features and locations, and away from those predictably associated with distractors (e.g., Geng & Behrmann, 2005; Golan & Lamy, 2022; Sha et al., 2017; Wang & Theeuwes, 2018). For example, if your friend often wears a green jumper or sits at a particular table in the canteen, then biasing attention towards the colour green or the location of that table is likely to help you find them. Selection history biases can operate across different timescales, have long-lasting effects, are flexible,

and do not require conscious awareness (B. A. Anderson et al., 2021; Chun & Jiang, 1998, 1999; Conn et al., 2020; Goujon et al., 2015; Jiang et al., 2013; Wolfe & Horowitz, 2017). This form of guidance, which exploits consistent structures in the environment with little effort, can be especially useful during everyday search tasks where many targets are neither physically salient nor preceded by explicit symbolic cues.

Together, bottom-up salience, top-down goals, and selection history are understood to each contribute to attentional deployment during visual search. Many popular models of visual search assume that these influences are integrated to produce a spatial priority map of the visual scene. In such models, locations are assigned levels of activation that determine the order in which attention is deployed between them. Items are processed in decreasing order of activation, until the target is found or search is abandoned (Liesefeld et al., 2024; Serences & Yantis, 2006; Wolfe, 1994, 2021). Although these priority maps are spatial in nature, they can reflect attentional biases based on both spatial and non-spatial item attributes. Earlier models emphasised bottom-up salience alone (e.g., Itti et al., 1998; Theeuwes, 2010), or jointly in combination with top-down sources (e.g., Cave & Wolfe, 1990; Wolfe, 1994; see also Zelinsky & Bisley, 2015), whereas the recent accounts also incorporate selection history (e.g., Awh et al., 2012; Wolfe, 2021).

Despite their value, many studies and models of visual search have important limitations. First, search involves not only the allocation of visual attention but also other cognitive processes, such as coordination of the motor system. This includes eye, hand, and body movements, the nature of which are typically directed towards the location of the target, or dictated by its features. The roles of these additional processes are often simplified or constrained in laboratory studies to isolate the main effects of interest (Hoffman, 1998; Hollingworth & Bahle, 2020). In the current thesis, Chapters 2 and 3 explore their individual contributions more specifically. Second, and of particular relevance here, most tasks require participants to search within static displays in which the number, identity,

and spatial arrangement of targets and distractors remains fixed throughout a trial (Boettcher et al., 2022; Wolfe, 2020). In contrast, many real-world environments are highly dynamic, meaning static tasks have only limited ecological validity. Moreover, such tasks often provide only temporally restricted measures of behaviour, typically capturing performance at a single time point per trial. These temporal limitations and recent approaches to overcome them are discussed further in Section 1.5 below.

Consistent with these static designs, many models of visual search have implicitly assumed that behaviour is guided by a fixed priority map constructed at the start of each trial and maintained throughout the search episode. However, as outlined in the following section, the influences underlying visual search behaviour are continuously evolving. Advancing our understanding of search therefore requires not only the use of more holistic measures and dynamic tasks, but also a conceptual shift towards treating search itself as a dynamic process and investigating the factors that modulate it over time (for similar arguments see Donk, 2021; Harding et al., 2021; Mohamed et al., 2023; Noonan & Störmer, 2023; Wolfe, 2021; Zhang et al., 2025).

1.2.1 Visual Search is a Dynamic Process

Even in static environments, the determinants of visual search behaviour are inherently dynamic. At longer timescales, performance changes across the lifespan, for example, due to ageing (e.g., Humphrey & Kramer, 1997; Ramzaoui et al., 2021; Shalev et al., 2024; Trick & Enns, 1998) or the acquisition of search-specific expertise (e.g., Carrigan et al., 2019; Robson et al., 2021). Search also evolves over shorter timescales. Across the course of an experiment, observers can become more efficient at identifying targets through practice effects, learnt predictions, and the tuning of attentional templates, while fatigue can slow search (e.g., Clark et al., 2015; Goldstein & Beck, 2018; Grady et al., 2022; Hout & Goldinger, 2010; Sireteanu & Rettenbach, 2000). From trial to trial, attentional templates are not persistently active but deactivate at the end of one trial and reactivate

before the next, reflecting a dynamic search system that cycles over the course of an experiment (Grubert & Eimer, 2018). Finally, within a single episode, it has historically been assumed that the factors governing search remain stable. However, as the following examples illustrate, the individual sources influencing visual search have their own temporal dynamics, which can cause behaviour to evolve over time.

At the onset of a search episode, attentional selection is dominated by early sensory signals. The influence of bottom-up attentional capture is largely limited to these earliest moments of search. It dominates attentional selection within the first few hundred milliseconds and, in free-viewing contexts, primarily affects only the first saccade (N. C. Anderson et al., 2015; Donk & van Zoest, 2008; Siebold et al., 2011). Another influence that appears confined to the early stages of search is short-term priming, such as when a target colour or location repeats across two consecutive trials (Maljkovic & Nakayama, 1994; Wolfe et al., 2022). In contrast, longer-term statistical learning has been found to impact not only early attentional guidance, but also to affect search at later times during trials, exerting a more persistent influence (Dolci et al., 2024).

As a search episode unfolds, goal-driven attentional guidance becomes increasingly influential relative to stimulus salience (Theeuwes, 2010). Although, the attentional templates underlying this top-down guidance can be active even prior to display onset (Grubert & Eimer, 2018). The time course of this search process can be impacted by the source of the attentional template. For example, guidance based on target attributes may operate differently from guidance based on distractor attributes. Addleman and Störmer (2022) reported that, while the enhancement of cued target features was found to be proactive, initiating before display onset, no evidence was found for proactive suppression of cued distractor features. Indeed, while the existence of proactive target enhancement is generally accepted, it remains debated whether distractors can ever be suppressed proactively, or only reactively after display onset (Geng, 2014; Luck et al., 2021; van Moorselaar &

Slagter, 2020; Wöstmann et al., 2022). Nevertheless, both positions are consistent with the view that understanding the temporal dynamics of guidance is crucial for progressing knowledge of how search unfolds (see also Zhang et al., 2025).

Search within a single episode continues to evolve across successive attentional deployments. As a trial progresses, attention is biased away from previously processed and rejected locations in the attentional priority map and toward novel ones, possibly through inhibition of return (Klein, 1988; Klein & MacInnes, 1999; Wolfe, 2021). Eye-movement patterns also evolve in free-viewing tasks: saccade amplitudes tend to decrease, while fixation durations increase, as a function of increasing saccade number (Godwin et al., 2014; Over et al., 2007). In hybrid foraging studies, where multiple instances of multiple target types are present, observers typically collect targets in runs of the same type. Here, the likelihood of selecting an item changes across the trial depending on the type of target previously selected, the length of the current run, and the number of targets remaining (Á. Kristjánsson et al., 2014; T. Kristjánsson et al., 2020; Wiegand et al., 2019). Beyond visual selection, decision-related processes also play out in time, for example, accumulating evidence about whether an item is a target and preparing the corresponding motor response.

Though not the focus of this thesis, it is worth noting that visual search unfolds within broader, ongoing temporal structures shaped by intrinsic brain and body rhythms (Nobre & van Ede, 2018). For instance, saccadic eye movements sample the environment rhythmically, at around 3Hz (Schroeder et al., 2010), and attention itself may operate under similar constraints, alternating between periods of more and less efficient cognitive processing at a rate linked to theta-band activity (Fiebelkorn & Kastner, 2019; Landau & Fries, 2012; VanRullen, 2016). Other physiological rhythms may also dynamically influence search, with visual sampling varying across the cardiac cycle (Galvez-Pol et al., 2020) and detection sensitivity fluctuating with respiration (Flexman et al., 1974; Kluger et

al., 2021). These findings suggest that the quality of our perceptual experience during visual search may not be continuous but fluctuate across multiple temporal windows.

Taken together, these examples illustrate that influences on visual search are not fixed, but evolve even within a single search episode. Static models of search, therefore, are inherently limited. Instead, the internal representations that guide search – attentional priority maps – are better understood as dynamic and shaped by temporal properties of their sensory and cognitive contributors (Liesefeld et al., 2024; Wolfe, 2021). Since the factors governing search *can* shift over time, a key question is whether within-episode changes are merely passive consequences of the temporal dynamics of biological and cognitive processes, or whether they can evolve adaptively to improve performance under specific task demands. The next two sections examine how this may be achieved through goal-relevant *temporal expectations*, while the penultimate section considers visual search in environments that are themselves dynamic.

1.3 Temporal Expectations

Attention has traditionally been studied as a process that unfolds across space, for example via static spatial priority maps during visual search. However, attention is inherently dynamic and, as such, can also be directed to moments in time. Coull and Nobre (1998) demonstrated this in a landmark study that employed a temporal analogue of Posner's (1980) classical spatial cueing paradigm (see also Kingstone, 1992). They found that explicitly cueing observers to a target's onset (either a short or long delay) sped responses to targets appearing at the cued time. Like much of the literature on temporal expectations, however, this study used isolated imperative stimuli rather than a visual search task. Before shifting our focus to understand how feature-temporal regularities may guide attention during visual search, we must first consider what is known about the capabilities of temporal expectations to guide behaviour more generally.

For the purposes of this thesis, temporal attention refers specifically to attention directed to particular moments in time, defined by intervals of absolute duration. This is distinct from research on the temporal limits of attention (see Nobre & van Ede, 2018) and from ordinal attention, which prioritises specific positions within a sequence (e.g., in serial reaction time tasks). Temporal and ordinal attention are closely related, as later ordinal positions naturally occur at later times, but they have been demonstrated to reflect different forms of expectation (Nobre & van Ede, 2018). To illustrate this distinction in the context of our real-world example: you might expect a friend to arrive at the canteen in two minutes, regardless of how many others arrive before them (temporal attention), or you may know their position in the queue for food and expect them to arrive after a certain number of others, regardless of timing (ordinal attention). Though both forms of expectations can guide attention and benefit performance, they have been found to operate independently and engage distinct neural substrates (Coull & Giersch, 2022; Kornysheva et al., 2013; Ullén & Bengtsson, 2003).

To investigate isolated effects of temporal expectations, it is important to avoid confounding them with ordinal expectations. Yet, it is unclear the extent to which temporal expectations can guide behaviour in the absence of predictable ordinal structure. Some studies suggest that benefits of temporal expectations occur only when combined with ordinal expectations (O'Reilly et al., 2008), and goal-irrelevant ordinal regularities may spontaneously capture attention more strongly than regularities in absolute timing (Damsma et al., 2020; Zhao et al., 2013). In everyday settings, however, temporally predictable events are often preceded by an unpredictable number of other events. A key question, therefore, is whether observers can abstract across unpredictable intervening events to exploit temporal regularities. The studies in this thesis address this by using dynamic tasks in which the predictable temporal intervals preceding an imperative stimulus are filled with an unpredictable number of other stimulus appearances, thereby disentangling the timing and order of stimuli.

1.3.1 Sources and Consequences of Temporal Attention

Expectations that guide attention across time can arise from multiple sources and have a range of consequences for perception, action, and cognition (see Nobre & van Ede, 2023). The following section outlines key sources of temporal attention, before considering their effects. One well-established source is explicit symbolic cues, which predict, or instruct, when targets will appear (Coull & Nobre, 1998). Such cues have been shown to guide temporal attention in a top-down manner. This leads to benefits for stimuli occurring at cued versus uncued intervals (e.g., Denison et al., 2017; Griffin, 2002; Miniussi et al., 1999; Rohenkohl et al., 2014). Another source of temporal expectations is rhythmic structure. In this case, attentional benefits are observed for sequential stimuli appearing at regular fixed intervals compared to variable intervals (e.g., Rohenkohl et al., 2012; Sanabria et al., 2011). Unlike the top-down guidance induced by explicit cues, rhythm-based guidance can be more stimulus-driven, occurring independently of predictive value (Breska & Deouell, 2014; Haegens & Zion Golumbic, 2018; Jones, 2015).

Other sources of temporal attention arise from expectations that build up over longer periods. One well-studied example is expectation formalised by the *hazard function*: the conditional probability of an event (e.g., a target) occurring at a particular moment, provided it has not yet occurred. In line with this function, attention is biased toward times with higher probability, yielding performance advantages for targets appearing at those times (Ghose & Maunsell, 2002; Grabenhorst et al., 2019; Janssen & Shadlen, 2005; Luce, 1986). In both experiments and everyday life, the likelihood of an event often increases with elapsed time, producing shorter RTs for targets that appear after longer delays (Coull, 2009; Niemi & Näätänen, 1981). This is exemplified by the expectation that a friend's imminent arrival at the canteen increases the longer that you are waiting for them.

More broadly, just as expectations can build dynamically with elapsed time, they can also be shaped by regularities learned across repeated encounters. While all aforementioned sources contribute to our ability to predict and prioritise events in time, the focus of this thesis is on these learnt predictions based on temporal regularities. Dynamic, real-world environments are often structured by events that unfold in predictable temporal patterns. Through selection history, these long-term associations can be learnt and used to predict when targets are likely to appear, biasing attention toward high-probability times and away from low-probability times, benefitting performance for targets at predicted moments (e.g., Cravo et al., 2017; Los et al., 2017; Olson & Chun, 2001). Returning to our canteen example, this would correspond to learning across days that a friend is likely to arrive two minutes after yourself, and accordingly focussing your search on that time window. While both hazard functions and learnt regularities underlie guidance that prioritises probable moments, the two differ in scope: hazard functions capture conditional probabilities that evolve within a trial, though their shape can be learnt across encounters, while learnt regularities reflect broader event-time distributions that need not be conditional.

As well as arising from diverse sources, there is an ongoing debate regarding the underlying mechanisms of temporal attention. Some researchers argue that the neural basis of temporal attention is a dedicated timing mechanism (an 'internal clock'), whereas others have suggested that temporal attention only influences behaviour by modulating the time course of other cognitive processes (for an overview see Nobre & van Ede, 2018). Regardless of the mechanism, temporal attention has been shown to consistently improve performance, primarily by enhancing accuracy and speeding responses (Nobre & van Ede, 2023; Seibold et al., 2023). The specific cognitive processes through which these benefits emerge, however, vary with task demands, stimulus attributes, and response requirements (van Ede et al., 2020).

At the early stages of visual processing, perception is facilitated at attended times and impaired at unattended times (Cravo et al., 2013; Denison et al., 2017; Fernández et al., 2019; Rohenkohl et al., 2012, 2014). This facilitation can improve visual acuity for temporally attended stimuli, particularly under perceptually demanding conditions (Correa et al., 2006; van Ede et al., 2020). Temporal attention also shapes oculomotor control: modulating anticipatory saccades when target location varies, and promoting saccade inhibition to stabilise fixation when target location is fixed (Boettcher et al., 2022; Denison et al., 2019; Pfeuffer et al., 2020; Tal-Perry & Yuval-Greenberg, 2020). Beyond perception and eye-movements, temporal expectations can speed the onset of decision-making processes and facilitate motor response preparation (Jepma et al., 2012; van den Brink et al., 2021; Volberg & Thomaschke, 2017; though see Korolczuk et al., 2018).

The influence of temporal attention may be broader than often assumed. For example, temporal attention does not only facilitate the processing and identification of targets, but it can also improve the handling of temporally expected distractors (Gresch et al., 2021; Lamy, 2005; van Ede et al., 2018; Wendt & Kiesel, 2011). In addition, while most evidence primarily relates to visual stimuli, as is most relevant to this thesis, many findings generalise across modalities. Indeed, similar, if not more consistent effects of temporal attention have been reported in audition (see Lange, 2013; Seibold et al., 2023).

1.3.2 Interactions Between Temporal and Non-Temporal Expectations

Researchers have examined temporal expectations not only in isolation, but also how they can be combined with expectations in other domains, such as space, features, and motor responses (for an overview see Seibold et al., 2023). These interactions can take different forms. For instance, attention can be guided based on co-existing expectations about temporal and non-temporal stimulus attributes that arise from independent sources, such as distinct symbolic cues (e.g.,

Kingstone, 1992; Doherty et al., 2005; Seibold et al., 2020). These simultaneous but distinct expectations may exert independent, additive, or interactive effects on behaviour.

By contrast, my work here focuses on more synergistic forms of expectation that jointly concern temporal and non-temporal attributes (e.g., Boettcher et al., 2022; Echeverria-Altuna et al., 2024; Thomaschke et al., 2016; Xu et al., 2021). For example, an expectation about stimulus location, or colour, that varies depending on when the stimulus appears. I refer to these temporally-contingent expectations about spatial locations and non-spatial features as *spatiotemporal* and *feature-temporal expectations*, respectively. Such expectations should cause attention to not be biased towards a particular location or feature value equally across time; instead, the passage of time itself serves as a cue for dynamically shifting attention within the relevant domain. Though temporal attention can prioritise processing at a specific moment in time, limitations in the visual system nevertheless prevent the processing of all information in a crowded dynamic scene at a given moment. Thus, temporal attention alone may be of limited utility in such contexts. Investigating how temporal attention can operate synergistically with spatial or feature-based attention is therefore especially valuable for understanding efficient real-world visual search.

Temporal and Spatial Expectations. Interactions between temporal and spatial expectations have been most widely studied. Here, research has produced mixed results (Seibold et al., 2023). Some studies suggest that temporal expectations may only enhance visual attention by amplifying the behavioural and neural effects driven by co-existing spatial expectations (Doherty et al., 2005; Rohenkohl et al., 2014). For example, Rohenkohl and colleagues (2014) found that valid temporal cues only benefitted performance when targets appeared at a validly cued location. Consistent with this view, research has shown that temporal attention can modulate activity in neurons with spatial receptive fields (Ghose & Bearl, 2010; Ghose & Maunsell, 2002), and regulate the timing of electroencephalography (EEG) event-related potentials (ERPs) associated with processing at

attended spatial locations (Seibold et al., 2020). Some models of temporal processing propose that temporal and spatial processing are intrinsically linked at the neural level (Buonomano & Maass, 2009; Cai et al., 2012), implying that spatial expectations are necessary for temporal expectations to be effective.

By contrast, other work points to largely independent influences of spatial and temporal expectations on visual stimulus processing. That is, spatial and temporal cues can independently modify behaviour (e.g., MacKay & Juola, 2007) with distinct differences in underlying neural activity (Coull & Nobre, 1998; Griffin et al., 2002). Task demands may account for these discrepancies: independent effects of temporal expectations may be possible, but masked in tasks where spatial cues provide the most informative guidance (see Seibold et al., 2023). Consistent with the view that spatial expectations are not a prerequisite for temporal attention, recent findings demonstrate that temporal expectations can guide behaviour even under spatial uncertainty (Echeverria-Altuna et al., 2024; Gao et al., 2025).

Although findings on the interaction between distinct spatial and temporal expectations have been mixed, studies of combined *spatiotemporal* expectations provide more consistent evidence. Unlike tasks in which temporal and spatial information are manipulated independently, spatiotemporal expectations link the two domains directly, such that the timing of an event predicts its spatial location. Under these conditions, temporal and spatial attention can operate together, dynamically guiding attention between locations. Of particular relevance to the current work, numerous studies have demonstrated that spatiotemporal regularities in which the interval preceding a target predicts its likely location can be used to guide visual attention, facilitating responses to targets at temporally likely locations (Boettcher et al., 2022; Pfeuffer et al., 2020; Rieth & Huber, 2013; Shalev et al., 2024; Wagener & Hoffmann, 2010; Xu et al., 2023, 2025).

Temporal and Feature-Based Expectations. In comparison to the more widely studied interaction between temporal and spatial expectations, the interplay between temporal and *feature-based* expectations remains relatively underexplored (see Seibold et al., 2023). In a pioneering study, Kingstone (1992) investigated interactions between two independent probabilistic cues: one which indicated the likely onset of a target letter, and the other its likely form. The results showed that the performance benefit of a valid form cue was reduced if the temporal cue was invalid, and vice versa, indicating that the effects of temporal and feature-based expectations can interact.

More recently, a handful of studies using non-invasive neuroimaging and electrophysiological methods in humans have provided converging evidence that temporal attention can enhance feature-based visual stimulus processing in a temporally tuned fashion. In an fMRI study, Warren et al. (2014) asked participants to detect a feature change in a continuously rotating Gabor patch. When participants were cued to a goal-relevant orientation at which the change was likely to occur, activity in orientation-sensitive voxels in the primary visual cortex shifted toward this orientation. Crucially, this tuning was time-selective, emerging just before the appearance of the cued orientation. Consistent with these findings, normalisation models of temporal attention propose that perceptual performance is improved through temporally tuned gain increases in units sensitive to target features, prior to stimulus onset (Denison et al., 2021; Ramirez et al., 2021).

Further, EEG studies have shown that temporal expectations can shape ERP indexes of feature-based attention. Grubert & Eimer (2018) manipulated the length of a predictable interval preceding a stimulus display onset and presented task-irrelevant probe stimuli in a pre-defined target colour at successive timepoints during this interval. They found that these probes elicited N2pc components, a measure thought to reflect attentional selection of lateralised visual stimuli, only when they appeared shortly before the expected display onset time. This is consistent with anticipatory temporal modulation of attention to the target colour. In a study using probabilistic

temporal cueing, Seibold et al. (2020) found that the presence of a stimulus in a pre-defined target colour, versus a non-target colour, enhanced N1 amplitude indicating attentional modulation only when it appeared at a validly cued time, and not at an invalidly cued time. Together, these findings suggest that temporal expectations may shape the neural dynamics of feature-based attentional deployment in a time-specific manner.

Other studies have explored the effects of combined feature-temporal expectations. In two studies, Thomaschke et al. (2016) and Wagener & Hoffmann (2010) used a foreperiod paradigm in which an isolated target appeared in one of two shapes or orientations most often following either a short or long delay (e.g., a diamond after 500 ms, an oval after 1600 ms). Both studies found faster and more accurate responses for identifying targets with temporally likely features compared to temporally unlikely ones. These findings are consistent with participants having learnt and used the regularities to update their feature-based expectations as the foreperiod progressed, changing their behaviour over time. However, in both studies these effects were not investigated in isolation from regularities in target location and/or motor response. Because spatial and motor-based expectations can also improve performance, and may support learning of temporal regularities, it remains important to establish whether feature-temporal expectations can effectively guide behaviour in their absence.

Addressing this gap, Echeverria-Altuna et al. (2024) and Gao et al. (2025) recently investigated the effects of predictable associations between target timing and features under both spatial and motor uncertainty. In extended trials, participants searched for colour-defined targets across two concurrent rapidly presented stimulus streams presented on either side of a fixation cross. Targets could appear in each of three colours, with participants cued to respond to just one colour at the beginning of each trial. Importantly, the likely timing of a target was inherently tied to its colour, with one colour likely to appear early in the trial, another likely to appear late, and the third

temporally unpredictable. Participants responded to targets by pressing a key indicating whether it appeared on the left or right of fixation. The spatial location of each target, and thus the required response, varied unpredictably across trials. Across experiments, targets in a temporally predictable colour were identified more quickly and accurately than targets in the temporally unpredictable colour. These findings show that incidentally learned feature-temporal regularities can be applied flexibly and in a goal-driven manner to guide behaviour, even when spatial and motor response information is uncertain. However, it is important to note that within these tasks, only one stream could contain a target or distractor stimulus at any given moment, while the other contained a neutral placeholder. This meant that no two stimuli appeared concurrently, inconsistent with classic definitions of a visual search task. This factor is critical, leaving it unclear whether feature-temporal expectations can operate effectively when multiple stimuli compete simultaneously for attention, as in naturalistic search scenarios.

Overall, this literature highlights the utility of temporal expectations in optimising not only spatial, but also feature-based processing of visual stimuli. The empirical work in this thesis investigates regularity-based feature-temporal expectations in a novel context: free-viewing dynamic visual search. In this setting, multiple stimuli compete for attention across a broad range of times and spatial locations. It remains unclear whether feature-temporal expectations can dynamically reweight attention between task-relevant features across a wide range of spatial locations within a noisy environment. Addressing this question will clarify if and how feature-temporal expectations can facilitate behaviour in busy, dynamic environments of everyday life.

Temporal and Motor-Based Expectations. Beyond perceptual modulation, temporal attention strongly influences motor processes. From early studies, temporal attention has been linked to action through both the behavioural outcomes and the underlying mechanisms. A consistent finding is that motor responses are faster when stimuli are temporally expected. Some

researchers have even argued that these effects only reflect temporal tuning of action preparation, rather than sensory modulation (Salet et al., 2022; Thomaschke et al., 2011; Thomaschke & Dreisbach, 2013; for an overview see Seibold et al., 2023). However, such effects can vary with task demands (van Ede et al., 2020). Neuroimaging and electrophysiological work has further shown that temporal attention can modulate brain activity related to response preparation, and that temporal expectations and motor processes share some common neural substrates (e.g., Coull & Nobre, 1998; Doherty et al., 2005; Griffin et al., 2001; Miniussi et al., 1999; Nobre, 2001; Rolke & Ulrich, 2010; Volberg & Thomaschke, 2017). These findings suggest that, similarly to spatial attention, action may play a critical role in forming, tuning, and applying temporal expectations to guide behaviour (Coull et al., 2024; Morillon et al., 2014; Morillon & Baillet, 2017; Shin & Ivry, 2002).

Like many everyday behaviours, visual search typically serves prospective actions, such as preparing a saccade or body movement towards a target. In contrast, laboratory studies of visual search rarely investigate actions directly, often minimising their role by requiring participants to maintain fixation and make only simple, prescribed responses (Nuthmann & Canas-Bajo, 2022; Zhang & Pan, 2022). The functional relevance of motor responses in visual search, together with the close link between temporal expectations and action, motivated aspects of Chapter 2 and 3. Chapter 2 investigates how temporal expectations for specific responses shape motor activity during visual search, operating alongside feature-temporal expectations that shape visual attentional guidance. Chapter 3 then separates these influences, examining how feature-temporal regularities influence search performance in both the presence and absence of effector-specific motor-temporal regularities.

This work relates to a broader question of whether temporal attention can exert a general influence on motor control (Cotti et al., 2011; Echeverria-Altuna et al., 2024; Kornysheva et al., 2013; Kornysheva & Diedrichsen, 2014), or whether its effects are restricted to operating in contingency

with effector- or action-specific motor plans (O'Reilly et al., 2008; Shin & Ivry, 2002; Volberg & Thomaschke, 2017).

1.3.3 Some Limitations Regarding Studies of Temporal Expectations

Most studies of temporal expectations and attention have used paradigms other than visual search. Most notably, many works have used a foreperiod paradigm in which an imperative stimulus is presented in isolation after a variable or fixed interval (the foreperiod) following a warning signal (e.g., Coull & Nobre, 1998; Kingstone, 1992; Thomaschke et al., 2016; Volberg & Thomaschke, 2017; Xu et al., 2023). This literature has been hugely informative for understanding how behaviour varies as a function of delay. However, the paradigm is relatively undynamic and thus limited in what it can reveal about how temporal expectations operate outside of the lab. As the foreperiod elapses, the display is typically blank, and the observer simply *waits* for the stimulus to appear. In reality, we are likely to be handling distracting information, and perhaps even performing secondary tasks, as we await a target event. These distractions may restrict our ability to accurately track time and employ temporal expectations effectively. To address this concern, the empirical work in this thesis employs variations of a dynamic visual search task (see Section 1.5) in which targets and distractors appear at different times and locations during trials. In these tasks, predictable temporal intervals preceding a particular stimulus are filled with transient and temporally unpredictable events.

A further limitation of many foreperiod studies is that they typically sample behaviour discretely, often with a single keypress at the end of each trial. Given that the fundamental characteristic of temporal attention is its dynamic nature, one can argue it is more informative to measure the effects of temporal attention by using measures that sample throughout a trial (for a similar argument see Nobre & van Ede, 2023). Some previous studies have achieved this through, for example, measuring responses to multiple stimuli presented sequentially during a single trial, or recording continuous eye-tracking or EEG data (e.g., Boettcher et al., 2022; Echeverria-Altuna et al.,

2024; O'Reilly et al., 2008; Salet et al., 2021). Building on this philosophy, experiments in this thesis address this limitation by collecting data relating to target responses (Chapter 4), fixations (Chapter 2), and motor activity (Chapter 2) at a wide range of timepoints throughout extended trials.

1.4 Temporal Expectations in Visual Search

Although temporal expectations are known to support adaptive behaviour in multiple ways, explorations of how they can facilitate visual search specifically are limited. This may relate to historical reliance on static visual search tasks and the assumption that the processes guiding a search episode remain constant over time. Yet, as previously discussed, visual search is inherently dynamic, and there are significant gaps in our understanding of how the determinants of search behaviour may evolve systematically over time in accordance with temporal expectations.

1.4.1 Ordinal Expectations in Visual Search

While not specifically addressing *temporal* expectations, several recent studies have examined how ordinal expectations arising from predictable between-trial associations can systematically influence visual search (Fougnie et al., 2015; A.-S. Li et al., 2023; A.-S. Li & Theeuwes, 2020; L. Wang et al., 2021; Wiegand et al., 2024). For example, Li & Theeuwes (2020) exposed participants to intertrial statistical associations whereby the location of a target in one trial was predictable from its location on the preceding trial. Participants were faster to respond to targets at predicted versus unpredicted locations, highlighting how regularities extracted across trials can bias behaviour. Similarly, L. Wang et al. (2021) reported reduced attentional capture by a salient distractor when it appeared at a location consistent with a predictable sequence of salient distractor locations across trials (though see A.-S. Li et al., 2023). Together, these findings suggest that observers can extract and exploit regularities across successive search episodes to proactively guide attention toward likely target locations and away from likely distractor locations.

Complementing this work, Zhao et al. (2013) demonstrated that ordinal regularities in a task-irrelevant stimulus stream presented prior to a search display facilitated the subsequent identification of targets that shared their location or features with stimuli in the stream. They concluded that these ordinal regularities had automatically captured attention, influencing subsequent search performance. By contrast, when Damsma et al. (2020) tested whether task-irrelevant stimulus streams containing regularities in absolute timing would have similar effects they observed no corresponding benefit for the search targets. This suggests that task-irrelevant temporal regularities do not automatically capture attention in the same way as ordinal regularities. Importantly, Damsma et al. (2020) only investigated the existence of *bottom-up* attentional capture by task-irrelevant temporal regularities, rather than guidance based on task-relevant temporal expectations.

These findings inherently relate to ordinal relations established outside of a given search episode – either between successive trials or before a particular trial. Consequently, while they demonstrate that expectations can guide behaviour adaptively over time, they do not reveal how expectations about the *absolute timing* of relevant events within a search episode can influence behaviour.

1.4.2 Temporal-Only Expectations in Visual Search

Visual search literature investigating guidance due to temporal expectations through top-down goals or selection history has often reported significant effects of temporal attention (Balke et al., 2021, 2022; Dietze & Poth, 2024; Grubert & Eimer, 2018; Lamy, 2005; Seibold et al., 2020; though see Seibold & Rolke, 2014; Szewczyk et al., 2022). Two ERP studies illustrate this point. In Seibold et al. (2020), participants were cued to expect a search display after either a short or long delay. ERP markers of spatial and feature-based attention were observed when displays appeared at the validly cued time but not at the invalid time. This indicates that cue-based temporal expectations modulate

the time window of activation for attentional selection processes during visual search. Grubert and Eimer (2018) similarly found that regularity-based expectations about display onset influenced the activation of feature-based attentional templates for a colour-defined target, examined with greater temporal resolution. The authors presented task-irrelevant coloured probe stimuli that either matched or mismatched the target colour at different intervals prior to the display onset. They posited that target-matching probes should elicit an N2pc, a marker of selective attention, only at times when the template was active. Their results indicated that templates were deactivated and reactivated between successive search episodes, activating approximately 1000 ms before display onset. Critically, the timing of this activation shifted later as the predictable interval between search displays increased. These findings demonstrate that temporal expectations about the onset of a *search display* can shape the timing of target-based attentional selection processes.

Temporal expectations may also aid distractor handling in visual search, though there is little work on this topic (Liesefeld et al., 2024). In an early study, Lamy (2005) manipulated the predictability of the delay between a task-irrelevant salient distractor that captured attention and the subsequent presentation of a visual search display. When this delay was fixed rather than variable, distractor-related effects on search performance were reduced or eliminated. This suggests that temporal expectations can help override attentional capture of salient distractors prior to a search display. Whether temporal expectations can also benefit the handling of distractors that appear within a visual search display is unclear. For example, Seibold & Rolke (2014) found that temporal preparation speeds overall responses but does not reduce distractor interference.

1.4.3 Spatiotemporal Expectations in Visual Search

Beyond purely temporal expectations, a small number of studies have investigated how *spatiotemporal* regularities influence visual search, where the likely location of a task-relevant stimulus varies predictably with time. Xu et al. (2023) used a foreperiod paradigm in which a static

search display appeared after either a short or long delay. Participants searched for a singleton target among distractors while maintaining central fixation and responded by reporting the orientation of a line inside the target. Stimuli could appear at six locations. Unbeknownst to participants, targets were more likely to appear at one location following the short foreperiod and at another location following the long foreperiod. The authors found performance benefits for targets at both high-probability locations overall, replicating previous work on *spatial* regularities in search. Interestingly, these benefits were time-sensitive: the effects associated with each location were largest when the display appeared after the foreperiod predictably associated with that location. These results suggest that participants learnt the task's spatiotemporal regularities and used them to guide attention dynamically more toward the most likely target location as the foreperiod elapsed. Related work showed that observers can also exploit spatiotemporal regularities to better handle salient distractors (Xu et al., 2021). Together, these studies provide valuable early evidence that the spatial priority map guiding visual search can evolve dynamically and adaptively as a function of time using learnt regularities. However, the simplistic and highly controlled nature of the foreperiod tasks used here, while producing isolated and often robust effects, limits their ecological validity and ability to capture behavioural changes with higher temporal resolution.

Boettcher et al. (2022) investigated whether spatiotemporal regularities can facilitate visual search in a more dynamic, extended setting. In their study, participants freely viewed a dynamic visual search display in which target and distractor stimuli (vertical and tilted grey bars, respectively) transiently appeared and disappeared, each fading in and out at a different time and location. Each trial contained eight targets, and participants were instructed to find and click on as many targets as possible as quickly as possible. Critically, half of the targets appeared at predictable times and within predictable spatial display quadrants, with each assigned a unique time-quadrant pairing, while the others were spatiotemporally unpredictable. Overall, the spatiotemporally predictable targets were

identified significantly more quickly and often than the spatiotemporally unpredictable targets. Because no one quadrant was overall more likely to contain a target, the authors concluded that this benefit reflected participants learning specifically which spatial quadrant to prioritise at different moments during trials. Consistent with this, eye-tracking measures revealed that participants' gaze was proactively biased toward the temporally likely target location throughout trials. The performance effects reported here have been replicated multiple times, with learnt spatiotemporal predictions found to benefit performance beyond effects attributable to single-trial priming or rhythmic attentional allocation, to be modulated by task demands (the number of distractors), and to facilitate behaviour across the lifespan (Boettcher et al., 2022; Shalev et al., 2022, 2024).

1.4.4 A Gap: Feature-Temporal Expectations in Visual Search

Although few studies have examined *spatiotemporal* regularities, previous work has not directly investigated whether *feature-temporal* regularities can influence visual search, dynamically biasing attention towards features at the moments they are most relevant. Some studies have addressed related but not equivalent questions. For example, Echeverria-Altuna et al. (2024) and Gao et al. (2025) reported benefits of feature-dependent temporal regularities in rapid serial visual presentation (RSVP) tasks. Further, Muhl-Richardson, Cornes, et al. (2018) and Muhl-Richardson, Godwin, et al. (2018) showed that ordinal regularities in colour sequences can shape behaviour in dynamically changing visual search displays. However, it remains unclear whether observers can use the elapsed time during a visual search episode (*when*) to predict the features of a goal-relevant event (*what*), irrespective of where the event occurs. The empirical work in this thesis addresses this gap by embedding task-relevant feature-temporal regularities in DVS tasks.

Investigating feature-temporal regularities in this manner is valuable for several reasons. Temporal expectations are already known to modulate cognitive processes operating in other dimensions, and learning of spatiotemporal regularities can dynamically adjust prioritisation of spatial

locations. Demonstrating similar effects for features would help to clarify the scope of temporal expectations in shaping the attentional priority map and guiding search behaviour. However, it is not obvious that such regularities can guide visual search when stimuli are not bound to specific locations. Echeverria-Altuna et al. (2024) recently demonstrated for the first time that feature-temporal predictions can influence behaviour under spatial uncertainty across two locations, yet other work suggests that temporal (Doherty et al., 2005) or ordinal (Wiegand et al., 2024) expectations support behaviour only when spatial location is also predictable.

In tasks where behaviour must be guided across a wide range of spatial locations, as in the tasks in this thesis and many real-world search contexts, it is uncertain whether spatial knowledge is a prerequisite for successfully extracting and using temporal regularities. Further, one proposed mechanism for the recently reported benefits of *spatiotemporal* predictions in free-viewing visual search is that they enable proactive preparation of saccades to temporally relevant locations, rather than solely reflecting underlying shifts in spatial attention (as noted by Xu et al., 2023). In such contexts, isolating temporal predictions from spatial ones may reveal more directly whether they can improve performance without relying on directional saccade preparation.

1.5 Introducing Dynamic Visual Search

1.5.1 Defining Static, Pseudo-Dynamic, and Dynamic Visual Search

Similarly to Boettcher et al. (2022), the work in this thesis will rely on *dynamic* visual search tasks. Tasks can be dynamic in different ways, and one might argue that even classical foreperiod designs are dynamic since fixation markers and static search displays appear and disappear across trials. Here, however, I focus on the extent to which the environment *within a single search episode* is dynamic.

I define *static* search tasks as those in which all targets and distractors are presented simultaneously, and all stimulus attributes remain unchanged throughout the trial (e.g., as in Xu et al., 2023). There also exist *pseudo-dynamic* tasks that involve only one or two discrete changes during a search episode, such as the delayed onset of a distractor following the appearance of the initial display (e.g., R. K. Lawrence et al., 2023; Yantis & Jonides, 1984). In contrast, *fully dynamic tasks* are those that involve extended trials in which the content of the visual search display evolves continually over time. Interest in such tasks has grown in recent years, reflecting a broader shift toward extending visual search frameworks into more immersive and ecological environments (e.g., Wolfe & Horowitz, 2017).

The present thesis is concerned with fully dynamic visual search tasks. Here, I aim to capture how search unfolds in evolving environments that more closely resemble everyday contexts, such as finding your friends in the canteen.

1.5.2 Previous Approaches to Dynamic Visual Search

Existing studies have varied how stimuli can change within and across different dimensions during fully dynamic search in several ways. One common approach has been to manipulate the locations of stimuli throughout individual search trials. This can be achieved by periodically replotting static items in new locations (Horowitz & Wolfe, 1998; Shi et al., 2020), or by introducing stimulus motion. The latter has been studied using both abstract moving stimuli (e.g., Boettcher & Nobre, 2025; Kunar & Watson, 2011) and more naturalistic dynamic environments (e.g., Bennett et al., 2021; Nuthmann & Canas-Bajo, 2022). Even within this class, studies have varied in whether the stimulus set remains constant during a trial (objects move but never disappear; e.g., T. Kristjánsson et al., 2022; Kunar & Watson, 2011), or evolves over time as items enter and exit the display (e.g., Bennett et al., 2021). Dynamic changes can also arise indirectly through self-initiated movement by the observer, such as during visual search tasks in immersive VR (e.g., Helbing et al., 2022; Zhang & Pan,

2022) or real-world environments (e.g., Draschkow & Võ, 2016). However, the tasks in this thesis are concerned primarily with allocentric changes in the display itself rather than with egocentric changes in perspective. Further, the DVS tasks in this thesis do not contain moving stimuli. This is intended to isolate the effects of feature-temporal regularities from other influences such as attentional capture by motion (Franconeri & Simons, 2003; Itti, 2005; Nuthmann & Canas-Bajo, 2022), smooth pursuit eye movements (see Kowler, 2011), or spatial predictability from motion trajectories (e.g., Doherty et al., 2005).

Another approach to make visual search tasks more dynamic has been to manipulate non-spatial features of stimuli during a trial. In such tasks, the same items (as defined by their spatial location) remain visible throughout a search episode but undergo changes in colour, shape, or luminance, either discretely or continuously (Kunar & Watson, 2011; Muhl-Richardson, Cornes, et al., 2018; Muhl-Richardson, Godwin, et al., 2018; Pilling, 2024). In some cases, these changes can determine an item's identity as either a target or distractor. This method can be a useful analogy for certain real-world contexts, for example when frying tofu and searching for golden brown pieces to remove from the heat. However, it does not reflect the dynamics of many everyday searches, where items typically maintain stable features within a single search episode.

Together, these prior approaches have demonstrated that both spatial and non-spatial dynamics can be introduced into laboratory search tasks. However, they have rarely been used to investigate how temporal expectations operate during search, leaving open the question of how people exploit temporal regularities in evolving environments.

1.5.3 Dynamic Visual Search as a Method for Investigating Temporal Expectations

Although few DVS tasks have been designed to directly test temporal expectations, an exception is Boettcher et al. (2022), who investigated whether spatiotemporal regularities could facilitate search in a dynamic, extended setting. In their task, participants freely viewed displays in

which targets and distractors (vertical and tilted grey bars) transiently appeared by fading in and out of a random-noise background. Their spatial location and features (other than opacity) remained constant. Importantly, stimuli appeared at a wide variety of locations and times throughout each trial, meaning the content of the search display evolved continually within a single trial.

This style of task offers several advantages for studying temporal expectations beyond traditional static paradigms such as foreperiod tasks. Like simpler designs, it still allows for controlled manipulation of temporal, spatial, featural, and motor regularities by systematically varying the likely onset times, locations, non-spatial features, and responses associated with certain stimuli across trials. At the same time, these DVS tasks allow for more flexibility. For example, the extended nature of trials permits multiple temporal regularities to be embedded within a single episode. By introducing staggered stimulus appearances within a trial this additionally provides opportunities for more response measurements and hence finer temporal resolution with which to track behaviour. Further, the free-viewing nature of the tasks enables researchers to test the influence of temporal expectations on eye movements over time.

Beyond these practical benefits, this style of task also offers greater ecological validity than static designs. By staggering transient stimulus appearances, the visible set of search items changes over time, resembling real-world search in dynamic environments. In extended settings like these, temporal expectations can guide behaviour *within* an ongoing search, unlike foreperiod designs where expectations concern the onset of the search display itself. The latter scenario is more akin to predicting when a photograph will appear before searching within it, whereas real-world search more often involves finding a target in an already unfolding, continuously visible scene. Static paradigms remain valuable for investigating proactive preparation of fundamental visual search processes, but studying within-episode temporal dynamics may provide more insight into how search unfolds in naturalistic settings. Finally, as mentioned previously, the inclusion of unpredictable stimulus

appearances between the temporally predictable ones allows temporal regularities to be unconfounded with regularities in stimulus order. This aspect of the design requires temporal regularities to be extracted across intervening and irregular events, further reflecting the potential challenges of using temporal structures to guide behaviour in real-world environments.

1.5.4 Dynamic Visual Search for investigating Feature-Temporal Expectations

The empirical work in this thesis uses a family of novel DVS tasks inspired by Boettcher et al. (2022), but with several important differences. First, to study *feature*-temporal rather than spatiotemporal regularities, stimuli varied in dimensions such as colour and shape, which were kept constant in Boettcher and colleagues' study. Targets and distractors were distinguished by these features, and multiple task-relevant feature values could appear within the same trial (e.g., multiple targets differing across colour). This allowed me to manipulate the likelihood that particular stimulus features would appear at given moments during trials.

Second, to isolate effects of feature-temporal regularities from effects of spatial ones, all stimulus locations were unpredictable. This design choice also allowed for eye movements to provide a more direct proxy measure of how attentional capture by stimulus features is modulated by temporal predictability, independently of directional saccade preparation (see Chapter 2).

Third, the predictable temporal structures themselves also differed from those in Boettcher et al. (2022). The number of predictable events per trial is reduced from four to two: an *early* and a *late* event. This simplified design combines the straightforward logic of foreperiod designs (e.g., Xu et al., 2023) with the ecological validity of extended dynamic search. Moreover, in contrast to Boettcher et al. (2022), not every temporally predictable event occurs on every trial, further separating effects of feature-temporal predictions from expectations surrounding the *order* of successive predictable events within a trial.

These principles were broadly applied across all experiments in this thesis, with variations employed to answer specific theoretical questions. Taken together, this family of tasks provides the first systematic investigation of whether and how feature-temporal regularities can be learned and used to guide behaviour during dynamic visual search. Beyond the theoretical insights, they also offer methodological contributions by extending the toolkit for using DVS tasks.

1.6 Aims of Thesis

In my doctoral research, I investigate how dynamic visual search behaviour is shaped by feature-temporal regularities – predictable associations between non-spatial, attention-guiding stimulus features and specific moments in time. By embedding such regularities into a continuously evolving, extended search task, I test whether people can learn and use these expectations to guide attention and action in complex environments.

1.6.1 Empirical Aims

Chapter 2 examines whether temporal regularities that jointly predict target features and motor responses can be learnt and used to adaptively guide dynamic visual search. Across two experiments, I assess effects on task performance, visual attention, and motor activity. In sum, my central theoretical aim is to test whether attentional capture to target-relevant features and motor activity throughout trials are tuned in accordance with the regularities.

Chapter 3 extends the findings of Chapter 2 by disentangling the contributions of various types of regularities. By using a task design that systematically manipulates the presence of purely temporal, feature-temporal, motor-temporal, and feature-motor-temporal regularities between participants, I aim to test whether each type of regularity can independently bias dynamic visual search performance.

In Chapter 4, my focus shifts to investigating how feature-temporal regularities can influence dynamic visual search when tied to distractors, rather than targets. Specifically, I investigate how the occurrence of transient distraction affects performance across an extended trial and how this cost might depend on feature-temporal expectations.

1.6.2 Methodological Aims

A central contribution of this thesis is the development of a novel set of DVS tasks. Across all empirical chapters, these tasks involve extended free-viewing trials in which targets and distractors appear transiently across varied times and locations. By varying stimulus colours while removing spatial predictability, the tasks allow for the controlled introduction of feature-temporal regularities. The designs also embed unpredictable stimulus appearances between predictable ones, ensuring that participants must extract temporal structure across noisy, evolving scenes. This provides a close temporal analogue to busy real-world search contexts.

A further methodological aim is to provide a temporally resolved account of within-trial dynamics. Extending beyond discrete accuracy and response time data, Chapter 2 employs more continuous measures: novel eye-tracking metrics capture shifts in attentional capture, and EMG recordings index modulations in motor tuning. In Chapter 4, an online DVS task with numerous targets presented throughout each trial provides another method for sampling behaviour over time. Together, these innovations provide both conceptual and methodological advances in the study of temporal expectations in visual search.

2 Feature-Temporally Predictable Targets Modulate Behaviour

2.1 Abstract

Recent research has investigated how temporal predictions modulate behaviour during visual search in dynamic environments. Spatiotemporal predictions have been shown to guide behaviour adaptively during search to improve target detection at temporally likely locations. The utility of non-spatial, feature-temporal predictions is relatively less explored. This chapter investigates whether and how behaviour may be guided toward feature-temporally predictable targets during visual search in crowded dynamic displays. Across two experiments, I tested 1) whether visual attention is guided toward target-relevant features in a temporally specific manner and 2) whether the motor system is temporally tuned accordingly. To examine this, I developed a free-viewing dynamic visual-search task in which participants searched for two distinct targets defined by non-overlapping colour-shape combinations. During an initial learning session, each target appeared at a predictable time. In a subsequent testing session, targets occasionally appeared at unpredicted times. Target locations were always unpredictable. I compared the efficiency of identifying targets appearing at predicted versus unpredicted times to test for performance benefits of feature-temporal predictability. In addition, I measured whether gaze fixation was captured by distractors that shared overlapping features with temporally predicted targets (Experiments 1 & 2). In Experiment 2, electromyography recordings were additionally used to test for anticipatory muscle activity tuned to the predictable target timings. The results indicate that learning feature-temporal regularities can dynamically modulate participants' efficiency in identifying targets, their feature-based attentional capture, and their muscle activity. These temporal tuning effects were sensitive to differences in trial structure

between experiments. This chapter highlights the flexibility of feature-temporal predictions and their potential to guide behaviour even under large spatial uncertainty. Additionally, the novel methodological approach laid the groundwork for further investigations into the effects of temporal predictions on visual search, detailed in subsequent chapters.

2.2 Introduction

Visual search is an effective experimental framework for investigating how our attentional system guides the selection of task-relevant stimuli amidst distraction. This guidance relies on the bottom-up saliency of stimuli in the environment, goal-based internal representations of target features, and learned environmental regularities (B. A. Anderson et al., 2021; Awh et al., 2012; Hollingworth, 2012; Wolfe, 2021; Wolfe & Horowitz, 2017). While most previous visual-search studies have focused on static environments (Wolfe, 2020), real-world settings are often dynamic, with targets and distractors appearing and disappearing from view at varying times. More recently, research has incorporated dynamic displays and begun to explore how temporal attention may facilitate target identification within these contexts.

Recent studies have explored how spatial attentional guidance operates in an adaptive, temporally contingent manner during visual search. In these studies, participants' performance benefitted from learning spatiotemporal regularities, whereby the temporal interval until target appearance predicted their likely spatial locations (Boettcher et al., 2022; Shalev et al., 2022, 2024; Xu et al., 2023, 2025). For example, Boettcher et al., 2022 demonstrated our ability to learn and use spatiotemporal regularities to aid target identification in dynamic and visually competitive environments. In their task, participants searched for targets among distractors while stimuli appeared and disappeared transiently at different times and locations during extended trials. Participants were faster and more accurate when identifying targets that consistently appeared at

the same time *and* location (e.g., a target that always appeared in the top left, two seconds into a trial) compared to targets that appeared at unpredictable times and locations.

In principle, spatiotemporal regularities may facilitate behaviour through various mechanisms. For example, studies have shown that learning spatiotemporal regularities leads to anticipatory eye movements towards temporally likely target locations (Boettcher et al., 2022; Pfeuffer et al., 2020). This suggests that we can learn and use spatiotemporal regularities to adaptively focus spatial attention over the course of search. Some behavioural benefits may result from enhanced response preparation, as well as oculomotor planning. Indeed, temporal expectations are known to act on the motor system, leading to faster responses to temporally expected, compared to unexpected, targets (Rolke & Ulrich, 2010; Thomaschke et al., 2011; Volberg & Thomaschke, 2017).

To better understand the utility of temporal predictions in guiding real-world behaviour, it is essential to consider whether temporally tuned behavioural guidance can also operate effectively under spatial uncertainty. Consider searching for two visually distinct targets in a dynamic scene. It is possible that each target appears with predictable timing but in an unpredictable location. In this case, dynamically shifting attention towards *features* of the temporally anticipated target, regardless of location, is likely more efficient than continuously attending to features of both targets equally. However, our ability to use such non-spatial, *feature*-temporal regularities to guide visual search behaviour is less well explored than its spatial counterpart. Though few in number, some studies have found initial evidence for attentional guidance based on feature-temporal regularities. Importantly, these studies have used tasks performed at fixation, where stimuli appeared in isolation at just one or two possible locations (Echeverria-Altuna et al., 2024; Gao et al., 2025; Thomaschke et al., 2016; Wagener & Hoffmann, 2010). This raises the question of how robust temporal guidance may be under greater spatial uncertainty.

This empirical chapter builds on these initial works by investigating feature-temporal guidance in a free-viewing dynamic visual search (DVS) task. Here, target and distractor stimuli could appear concurrently and in locations spanning the display, requiring feature-based attention to operate selectively over a wide spatial range. In two experiments, I investigated whether participants could utilise feature-temporal regularities embedded within the task to guide their behaviour in this busy dynamic environment filled with unpredictable distraction. This chapter therefore extends our understanding of whether regularity-based feature-temporal predictions can effectively guide attention in real-world settings where these demands are commonplace. These experiments also further previous work by continuously recording eye movements (Experiment 1 & Experiment 2) and hand muscle activity (Experiment 2) throughout each trial, in addition to more traditional target-based performance metrics captured at a single time point. These additional measures allowed me to examine more directly the dynamic effects of temporal predictions on underlying attentional capture and motor preparation processes during search.

During DVS trials in both experiments, participants searched through stimuli (coloured shapes) that appeared transiently at different times and locations for two distinct targets among distractors, identifying targets with a key press. Targets had non-overlapping identifying features, while distractors shared zero or one feature with each target. Critically, during the initial learning session, each target appeared predictably at either an early or late moment during the trial, with exact trial timings differing between experiments. Temporally invalid targets were introduced in the subsequent testing session. Independently across all experimental trials, each target stimulus was equally likely to appear, and a target appearance was equally likely to occur early or late. However, taken together, the timing of a target appearance predicted the likely target stimulus.

In both experiments, I first used behavioural measures to test whether the feature-temporal regularities influenced participants' performance in identifying targets. To elucidate the mechanisms

underlying behavioural benefits of feature-temporal predictions, I then used eye tracking to test whether gaze would be captured most by distractors that shared an identifying feature with the temporally predicted target. Such a finding would indicate the presence of temporally-tuned feature-based attentional capture. Additionally, in Experiment 2, I used electromyography (EMG) data to test whether feature-temporal regularities resulted in anticipatory temporal tuning of motor preparation to respond to the temporally predicted target.

To foreshadow the results, learning feature-temporal regularities was found to dynamically tune participants' performance in both experiments and to modulate their feature-based attentional capture and anticipatory motor activity in Experiment 2. These results provide evidence that humans can utilise non-spatial feature-temporal regularities to guide multiple aspects of behaviour while searching for targets in busy dynamic environments filled with unpredictable distraction.

2.3 General Methods

Experimental procedures were largely consistent across Experiments 1 and 2, with general methodologies described below. Experiment-specific methods are detailed in Sections 2.4.1 and 2.5.1, respectively.

2.3.1 Participants

I recruited participants aged between 18 and 40 who reported normal or corrected vision (including colour vision), fluency in English, no history of neurological or psychiatric disorder, and not taking any psychoactive medication. All participants gave informed consent. Participants received either financial compensation (£15 per hour) or course credits. All experimental procedures were reviewed and approved by The University of Oxford Medical Sciences Interdivisional Research Ethics Committee. Sample sizes differed between experiments.

2.3.2 Apparatus

Participants sat positioned on a chin rest approximately 95 cm from the monitor (27-inch (68.58 cm) Acer XB270H, refresh rate 100 Hz, 1920 x 1080 pixels resolution). The Eyelink-1000-plus desktop mount (SR Research, Ontario, Canada) was used to record eye movements at 1000 Hz. I used a 9-point calibration routine with an error threshold of .5 degrees of visual angle. Drift correction was applied between each block. When necessary, participants were recalibrated before beginning the next block of trials. The experimental scripts were generated using *MATLAB* (MATLAB v2020a; The MathWorks Inc, 2020) and is available on OSF (https://osf.io/jbd86/files).

2.3.3 A Novel Dynamic Visual Search Task

Stimuli. The search display contained a selection of the stimuli, illustrated in Figure 2.1A. They appeared at various times and locations on a static greyscale 1/F noise background (Figure 2.1B). A video demonstration of a trial can be found here: https://osf.io/jbd86/files. Backgrounds were uniquely generated for each trial. This stimulus set consisted of all combinations of three distinct colours ('pink' (RGB (255,132,255); 'blue' (RGB (1, 230, 207); and 'orange' (RGB (255, 147, 0))) and three distinct shapes drawn from equidistant points in the Validated Circular Shape Space (A. Y. Li et al., 2020). Each stimulus was sized to fill a 54 x 54-pixel box on the display, approximately equal to one degree of visual angle (DVA) square. The total number of stimuli appearing in each trial differed between experiments.

Participants were assigned two stimuli as their targets. Targets differed in both colour and shape. The assignment of three possible target pairs was balanced across participants. The pairs were [1A and 2B], [1C and 3A], or [2C and 3B] and are pictured in Figure 2.1A. The seven non-target stimuli appeared as distractors. Each distractor shared either zero or one feature (colour or shape) with each target.

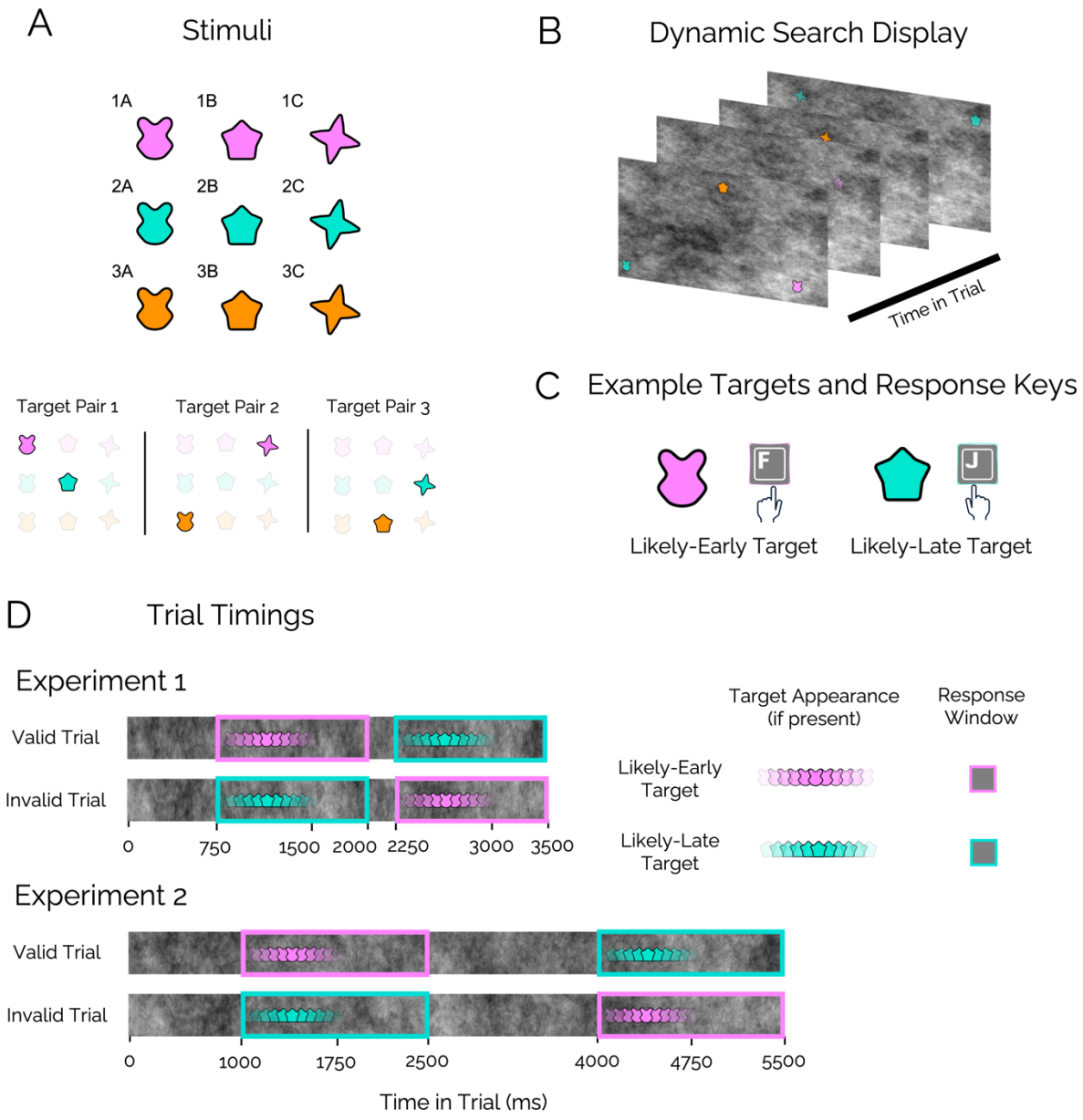


Figure 2.1. DVS schematic. (A) The nine coloured shape stimuli that appeared as targets or distractors during visual search trials and the three possible target pairs whose assignments were balanced across participants. **(B)** Illustration of a single DVS trial. The coloured shape stimuli transiently faded in and out of a static noise background at different locations and times during the trials. A video demonstration of a trial can be found here https://osf.io/jbd86/files. **(C)** Example pair of target stimuli, along with their associated response keys and temporal predictabilities. For illustrative purposes, this example is referenced throughout this chapter. **(D)** Schematic of trial timings in Experiment 1 and Experiment 2, for valid trials (top row) and invalid trials (bottom row). Whenever a target appeared, it onset at either 750 ms or 2250 ms in Experiment 1, and at either 1000 ms or 4000 ms in Experiment 2. After onset, targets were visible for 750 ms, and participants had 1250 ms in Experiment 1, and 1500 ms in Experiment 2, to respond correctly.

General Timings. Stimuli faded in from zero to the maximum opacity of 0.75 over 250 ms, remained at maximum opacity for 250 ms, and then faded out to zero opacity over 250 ms. The total duration during which stimulus opacity was greater than zero was therefore 750 ms. The 'onset time' of a stimulus is defined as the time the stimulus *began* fading in, relative to the beginning of a trial. Importantly, onset time did not necessarily equate to the onset of stimulus visibility for a participant. The length of trials differed between experiments.

Target Timings (Predictable). Each of the two possible targets in a trial appeared at a predictable early or late onset time. One of the targets, the 'likely-early target', was most likely to appear at the early onset time, while the other, the 'likely-late target', was most likely to appear at the late onset time (Figure 2.1C and Figure 2.1D). The exact probabilities of the targets' onset times depended on the experimental session (see Learning and Testing Sessions). I did not inform participants of these regularities. The assignment of each target as the likely-early or likely-late target was counterbalanced across participants.

Distractor Timings. Distractors were temporally unpredictable. On each trial, the onset time for each distractor was randomly selected, without replacement, from a list ranging from the earliest possible onset time to the latest, in 100 ms steps. The earliest and latest possible onset times varied between experiments, however, across both experiments, the assignment resulted in a consistent average level of visual distraction throughout trials. While no distractor was permitted to appear within 100 ms of another distractor, or a target, multiple stimuli could be visible concurrently given the 750-ms stimulus duration.

Stimulus Locations. All target and distractor stimuli were spatially unpredictable across trials. Stimulus locations were pseudo-randomly assigned on each trial. Specifically, locations were assigned such that a stimulus could appear anywhere on the display, provided that none of its edges were

within 54 pixels (approximately one DVA) of another stimulus or the edge of the display. The location of each stimulus remained constant as it faded in and out.

Identifying Targets. Participants were tasked with finding all targets that appeared during a trial. They were instructed to report targets with a key press as quickly as possible. One target required an 'F' response, while the other required a 'J' response (e.g., Figure 2.1C). I counterbalanced the assignment of response keys to each target (likely-early or likely-late) across participants. Participants had a limited time window following target onset to provide a correct response. The length of this response window varied between experiments (Figure 2.1D). Any responses made outside of this window were classed as false alarms. Participants were aware that both targets, one target, or no targets could appear on any given trial but were not instructed how many targets to expect on a specific trial.

Feedback. After each trial, feedback was provided. "Correct" was displayed whenever correct responses were made to all targets and no false alarms occurred. "Incorrect" was displayed when participants missed a target, responded with the incorrect key, or made a false alarm.

Learning and Testing Sessions. Unbeknownst to participants, they completed a learning session followed by a testing session. The number of blocks in each session differed between experiments. Each block had 100 search trials randomly intermixed: 25 trials with no targets, 25 with only the likely-early target, 25 with only the likely-late target, and 25 with both targets. Each target, therefore, appeared in an equal number of trials overall.

During learning trials, the time when each target appeared was entirely predictable. If the likely-early target appeared, it always onset at the early onset time. If the likely-late target appeared, it always onset at the late onset time. All learning trials were 'valid' trials.

During testing, target timings were less predictable. Onsets were preserved in 72% of target-present trials ('valid' trials) and reversed in 28% of target-present trials ('invalid'). Whenever a

particular target appeared during an invalid trial, it appeared at the onset time previously associated with the other target. In other words, the likely-early target onset late and the likely-late target onset early. Figure 2.1D depicts the target timings and response windows for valid and invalid trials in each experiment.

2.3.4 Procedure

Participants first provided informed consent and demographic information before reading the DVS instructions. They then completed a short training session to ensure they knew their targets and response keys. During each of 28 training trials, participants were shown a coloured shape and instructed to respond using the appropriate 'F' or 'J' key only if that stimulus was a target. Each target was shown seven times and each distractor twice. Participants were required to get 80% of training trials correct to progress, or the session repeated.

Following training, participants completed 16 practice trials of the DVS with valid target timings. These included four trials in which both targets appeared, four with only the likely-early target, four with only the likely-late target, and four target-absent trials, randomly intermixed.

2.3.5 Variables of Interest

Across both experiments, data analysis addressed two questions. The first question was whether participants learned and used the feature-temporal regularities to guide performance. Behavioural data from the testing session most directly addressed this question by testing for performance benefits to identify targets appearing at valid versus invalid onset times. The second question was whether goal-related internal templates of the target features guiding search were present and temporally tuned according to the task regularities. To address this, I used eye tracking to measure how fixations on distractors during target-absent trials in the learning session changed depending on whether they shared identifying features with the temporally predicted target. In Experiment 2, data analysis served a third goal: to investigate whether motor activity related to each

target response became temporally tuned to the predictable target timings (see Learning Session: Temporally Tuned Response Activity).

Testing Session: Performance Measures of Feature-Temporal Expectations. The inverse efficiency score metric (IES; Townsend & Ashby, 1983) was chosen as the dependent variable of interest. The IES combines accuracy and response time (RT) into one metric. IES was calculated by dividing the mean RT by the proportion of target hits. Lower IES thus indicated more efficient performance. Hits were a binary measure indicating whether a target had been correctly identified within the time limit (hit; 1), or not (0). RTs were calculated as the time, in ms, between the onset of a target and the first correct key press which resulted in a hit. As such, a correct classification (hit) was contingent on RT speed. Correct key presses outside the response window were not counted as hits. The IES metric, which combines hits and RT, was, therefore, especially useful for this study.

The two main independent variables of interest were *target onset* (early or late) and *target likelihood* (likely-early or likely-late). For each participant, I calculated the IES for targets at each combination of levels of these variables (corresponding to each bar in Figure 2.4). In Experiment 1, these levels were further split by *testing block number* (one, two, or three), meaning 12 IES values were calculated per participant in total (corresponding to each bar in Figure 2.2). Likely-early targets with an early onset or likely-late targets with a late onset were considered valid. In contrast, likely-early targets with a late onset or likely-late targets with an early onset were considered invalid. I hypothesised that, if participants utilised regularity-based predictions, performance should be more efficient when identifying temporally valid versus invalid targets.

I omitted targets that appeared second during two-target trials from the analysis because the identity of the second target could be considered cued by the identity of the first target. Omitting these targets avoided conflating behavioural effects due to this identity cueing with effects due to temporal predictions.

Learning Session: Feature-Temporal Capture by Distractors. Attentional capture by distractors sharing features with the targets offered a means to test whether participants used regularity-based temporal predictions to tune their visual attentional guidance to relevant features. Specifically, I tested whether eye movements were differentially directed toward the features (colour and shape) of the likely-early target versus the likely-late target at different times throughout trials.

Visual fixations on individual distractor stimuli were the dependent variable that served as a proxy measure of attentional capture. Fixation was a binary measure indicating whether a distractor was fixated (1) or not (0). The premise was that a fixated distractor had captured more attention than a non-fixated distractor (Hollingworth & Bahle, 2020). Fixations were considered as being on a distractor if they occurred within 107 pixels (two DVA) of the stimulus centre and began during the distractor's 750-ms appearance. Here, I used the fixation events and their corresponding start times and average spatial positions recorded by EyeLink. Distractors were classified by whether they shared each feature (colour or shape) with the likely-early, likely-late, or neither target. This resulted in two factors per distractor (*colour type* and *shape type*) with three levels each (likely-early target match, likely-late target match, or no match). Figure 2.3A illustrates the distractors at each level of colour type for the example targets. Additional independent variables were the distractor's onset time and the learning block number. Note that here I considered the onset time of each distractor within the trial, rather than the time within the trial when a fixation began. This was because my fixation measure was defined at the stimulus level, and aligning fixations to distractor onset times enabled more direct comparisons with the target regularities which were also defined in terms of stimulus onset.

For both experiments, a preliminary analysis determined which target features, colour and/or shape, participants used to guide attention. I compared the probability of fixating a distractor that either shared or did not share colour or shape with a target. If a particular target feature captured

attention, then the distractors with that feature would be more likely to be fixated. Based on this assumption, the preliminary analysis for both experiments suggested that participants overwhelmingly used target colours, more so than target shapes, as a basis for attentional guidance during the DVS. Therefore, the remainder of the analyses focused on colour type, rather than shape type. Results of these preliminary analyses for Experiments 1 and 2 are visualised in Supplementary Figure 7.2 and Supplementary Figure 7.6, and their output is given in Supplementary Table 7.4 and Supplementary Table 7.8, respectively. Further analyses of shape type for Experiments 1 and 2 are also provided in Supplementary Figure 7.4 and Supplementary Figure 7.8 and Supplementary Table 7.5 and Supplementary Table 7.9, respectively. Full scripts for these analyses are provided on OSF (https://osf.io/jbd86/files).

The subsequent, central analysis compared the difference in fixation likelihood between distractors that shared their colour with the likely-early target versus the likely-late target across onset times and learning blocks. I hypothesised that if feature-based attentional guidance followed the task regularities, then distractors that shared their colour with the likely-early target would more likely be fixated when they appeared early in the trial. In turn, distractors that shared their colour with the likely-late target would more likely be fixated when they appeared late. Additionally, this pattern of results should become more pronounced during later learning blocks, as participants gained exposure to the temporal regularities.

Only data from target-absent trials in the learning session were analysed. Target-absent trials were analysed because they provide the most direct measure of colour-based attentional capture without contamination from changes in strategy or motivation related to finding a target. Learning session trials were analysed to avoid effects related to changes in temporal predictions following the introduction of temporally invalid targets in the testing session. Analysis was further restricted to

distractors that appeared for the full 750 ms (i.e., distractors with an onset time after 0 ms and at least 750 ms before the end of a trial).

2.3.6 Statistical Analysis

All analyses used R (R Core Team, 2024), and plots were created using the *ggplot2* package (Wickham, 2016). Full datasets, and data cleaning and analysis scripts, are available on OSF: https://osf.io/jbd86/files.

Data Cleaning. Cleaning of behavioural performance data from the learning and testing sessions followed the same procedure, performed separately. If a participant's learning session data were excluded, then so were their testing session data, and vice versa. I replaced all data, including any eye-tracking and EMG data, from excluded participants and repeated data cleaning until the pre-determined sample size was reached.

Data from participants with low accuracy were excluded. The accuracy threshold for inclusion consisted of identifying at least 50% of all targets in both learning and testing sessions. Data were also excluded if the participant's mean accuracy was below 3 standard deviations (SDs) of the mean accuracy across all participants in either session. I planned to exclude any participant whose proportion of false alarms was greater than 50% across all key presses, or more than 3 SDs from the mean proportion across all participants. However, no additional participants were excluded. False-alarm proportions were low, comprising on average 7.66% and 5.64% of key presses in the final participant samples for Experiments 1 and 2, respectively.

On the target level, data were processed to remove premature or outlier responses. Data with RT < 200 ms were removed. In addition, responses were removed if the RT was slower than three standard deviations from the individual's overall median RT. I planned to exclude data from any participant with more than one third of trials removed, or whose median RT was more than 3 SDs

away from the median RT across all participants in either session. However, this excluded no further participants.

Testing Session: Behavioural Performance. I analysed the IES values using a repeated-measures analysis of variance (ANOVA) test, using the *ezANOVA* function from the *ez* package (M. A. Lawrence, 2016). Before analysis, IES values were transformed to meet the assumption of normality using the *boxcox* function of the *MASS* package (Venables & Ripley, 2002). In all cases, a two-tailed 5% error criterion was used to test for significance. Following any significant interactions between target likelihood and onset time, I conducted further pre-planned *t*-tests separately analysing the effect of target likelihood at each onset time. These comparisons were supplemented by Cohen's *d* values, calculated using the untransformed IES values, and by paired Bayesian *t*-tests on the transformed values using the *BayesFactor* package (Morey & Rouder, 2022). I used *BayesFactor*'s default prior ($r = 0.707$) to test the null hypothesis of no difference between the two sets of values against the alternative hypothesis that there is a difference. Interpretations for different Bayes factor (BF_{10}) values are given in Table 2.1 below.

Table 2.1

Bayes Factor Value Interpretations

Value Range	Evidence Strength
$BF_{10} > 10$	Strong in favour of H_1.
$3 < BF_{10} < 10$	Moderate in favour of H_1.
$1 < BF_{10} < 3$	Anecdotal in favour of H_1.
$0.33 < BF_{10} < 1$	Anecdotal in favour of H_0.
$0.1 < BF_{10} < 0.33$	Moderate in favour of H_0.
$BF_{10} < 0.1$	Strong in favour of H_0.

Note. H_1 and H_0 denote the alternative and null hypotheses, respectively.

Learning Session: Distractor Fixations. Generalized linear mixed-effects models (GLMM) with binomial distribution tested for effects on distractor fixations. Mixed-effects models can model the contributions of both fixed effects, related to the independent variables, and random effects, related to differences between participants, and related to variation in the dependent variable (Harrison et al., 2018). Mixed-effects models are also believed to be robust against unbalanced conditions (Kliegl et al., 2010), such as present in my designs. I ran the GLMMs using the *glmer* function of the *lme4* package in R (Bates, Mächler, et al., 2015). The model contained fixed effects for colour type, onset time, learning block number, and their interactions.

Onset time and block number entered the model as centred and scaled continuous predictors. I applied custom contrasts to the colour type factor, details of which are given in

Supplementary Table 7.3. These contrasts allowed for two separate comparisons of the three levels of colour type, which are illustrated in Figure 2.3A. The first contrast, the '*goal-dependent contrast'*, compared fixation rates between distractors that *did not* versus *did* share their colour with any target (no colour match vs. target colour match). This comparison determined whether distraction fixations provided a sensitive measure of goal-dependent feature templates. Following this confirmatory analysis, the main comparison of interest was between distractors that shared their colour with the *likely-early* versus the *likely-late* target (likely-early vs. likely-late target colour match). This comparison was specified by the second contrast, the '*prediction contrast*'.

I selected the random-effects structure of the optimal GLMM in line with suggestions by Bates, Kliegl, et al., (2015). The random-effects structure of the initial, full model included intercepts for all participants and by-participant slopes for the effects of colour type, onset time, block number, and all interactions. I tested this full model for over-parameterization using a principal component analysis (PCA) of the random-effects variance-covariance estimates. Here I employed the *rePCA* function of the *lme4* package (Bates, Mächler, et al., 2015). If the model was over-parameterised, I reduced it by removing the random effects component that explained the least variance and did not contribute significantly to the model goodness-of-fit, as indicated by a likelihood ratio test. This process was repeated until I found the optimal model (as reported in the results), for which all random-effects components were supported by the PCA and contributed significantly to the goodness-of-fit.

The results section focusses on predictors relating to the goal-dependent and prediction contrasts of the colour type variable. Here, I report regression coefficients, β, alongside the *z*-statistic, and the standard error (*SE*). The *p*-values are based on asymptotic Wald tests. I used a 5% error criterion to test for significance. Pre-planned additional mixed models helped clarify any significant interactions between the prediction contrast, onset time, and/or block number. These additional

models separately analysed the effect of the prediction contrast for 'early' and 'late' onset times, and/or for the first and final learning blocks, respectively. Here, I defined distractor onset times as early or late according to whether they fell before or after, respectively, the midpoint between target onset times. Further, to help balance the number of distractors classified as early or late, the same range of onset times were covered by each category. For Experiment 1, early onset times fell between 250 ms and 1500 ms, and late onset times between 1500 ms and 2750 ms. For Experiment 2, early onset times fell between 250 ms and 2500 ms, and late onset times between 2500 ms and 4750 ms (Figure 2.5 Block 4).

2.4 Experiment 1

In Experiment 1, the main goals were to 1) find initial evidence that feature-temporal regularities can guide dynamic visual search performance and 2) test more specifically whether these regularities can guide visual attention. To this end, I compared performance in the testing blocks for valid and invalid targets and compared eye-movement patterns in learning blocks.

2.4.1 Methods

Participants. The final sample consisted of 36 participants (26 female, three non-binary, seven male; mean age = 24.20 ± 5.44 (SD)). Two additional participants were tested, but their data were excluded for low accuracy. This sample size was partly selected to meet counter-balancing requirements as a multiple of 12. It also had power of at least 80% for detecting a medium-large effect of target predictability on performance in a repeated-measures *t*-test with a significance criterion of .05, as indicated by a *G*Power* analysis (G*Power 3.1; Faul et al., 2007). This was based on effect sizes of target predictability observed in previous statistical learning literature (e.g., Boettcher et al., 2022; Wagener & Hoffmann, 2010).

Stimuli. During every trial, exactly nine stimuli appeared. Zero, one, or two were targets. Each target appeared no more than once in a trial. Each distractor stimulus appeared at least once per trial. In trials where zero or one targets appeared, two or one randomly selected distractors, respectively, appeared a second time.

Trial Timings. All trials lasted 3500 ms. The early target onset time was 750 ms and the late target onset time was 2250 ms. Participants had a window of 1250 ms following target onset to provide a correct response. This response window lasted 500 ms after the disappearance of the target, to allow for post-stimulus processing and late responses. All distractor onset times fell between -650 ms and 3450 ms. The negative onset times served as dummy values to allow distractors to be part-way through their appearance at the start of a trial.

Procedure. After practice, participants completed either five or eight blocks of the DVS task. Experimental sessions lasted approximately 60 or 90 minutes, respectively. All 36 participants completed a five-block learning session with 100% valid targets. Twenty-four of these participants (18 female, two non-binary, four male; mean age = 24.38 ± 6.27 (SD)) then completed a three-block testing session with 72% valid targets. Participants could take breaks lasting up to three minutes between blocks.

Statistical Analysis. ***Data Cleaning.*** RT data cleaning removed 0.41% of data from the learning session and 0.38% from the testing session.

Testing Session: Behavioural Performance. I analysed the IES values from the 24 participants that completed the testing session using a 2 x 2 x 3 (onset time x target likelihood x block number) repeated-measures ANOVA test. As I had no specific hypotheses about the effects of block number during testing, any significant interactions of block number with onset time and/or target likelihood were followed up with additional tests using Bonferroni-corrected alpha values.

For completion, supplementary analyses assessed the effects of target likelihood, onset time, and block number on hits and RT individually. Results of these analyses are visualised in Supplementary Figure 7.1 and provided in Supplementary Table 7.1 and Supplementary Table 7.2.

2.4.2 Results

Testing Session: Performance Benefits for Feature-Temporally Predictable Targets. In line with *boxcox* recommendations, IES values underwent a reciprocal squared transformation prior to analysis. The ANOVA revealed a significant main effect of target likelihood (p = .003). Overall, participants were more efficient at identifying the likely-early target (M_{IES} = 1025 ms, SD_{IES} = 168 ms) than the likely-late target (M_{IES} = 1151 ms, SD_{IES} = 168 ms). Of interest, the ANOVA also revealed a significant two-way interaction between target likelihood and onset time (p = .007) and a significant three-way interaction between these two variables and block number (p = .031; Figure 2.2). All other predictors were non-significant. The full ANOVA output is given in Table 2.2.

I followed up the significant three-way interaction by running three additional repeated-measures 2 x 2 (onset time x target likelihood) ANOVAs. I investigated for which of the three testing blocks the interaction was significant, using a Bonferroni-corrected significance level of .017. The ANOVA for the first testing block revealed a significant interaction between target likelihood and onset time (F(1, 23) = 11.85, p = .002, η^2 = .051). In contrast, no significant interaction was found for the second testing block (F(1, 23) = 3.68, p = .068, η^2 = .019) or the third testing block (F(1, 23) = 0.02, p = .903, η^2 < .001). For the full reports on these additional ANOVAs please see the analysis scripts on OSF (https://osf.io/jbd86/files).

For testing block one, two follow-up repeated-measures t-tests separately analysed the effect of target likelihood at each onset time. When targets onset at 750 ms, target likelihood significantly affected IES, t(23) = 4.93, p < .001, d = 0.75, BF_{10} = 28.89. As hypothesised, participants were more efficient at identifying the temporally-valid likely-early target (M_{IES} = 977 ms, SD_{IES} = 302

ms) than the temporally-invalid likely-late target (M_{IES} = 1299 ms, SD_{IES} = 302 ms). In contrast, when targets appeared at 2250 ms, target likelihood had no significant effect on IES $t(23) = 0.09$, $p = .933$, $d = 0.17$, $BF_{10} = 0.22$, though numerically this effect trended in the expected direction.

Table 2.2

Experiment 1 Testing Session IES Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	1.66	1	23	.210	.002
Target Likelihood	**11.34**	**1**	**23**	**.003**	**.060**
Block Number	2.55	2	46	.089	.008
Onset Time : Target Likelihood	**8.94**	**1**	**23**	**.007**	**.014**
Onset Time : Block Number	0.15	2	46	.863	< .001
Target Likelihood : Block Number	0.81	2	46	.452	.003
Onset Time : Target Likelihood : Block Number	**3.76**	**2**	**46**	**.031**	**.009**

Note. Significant predictors are shown in bold.

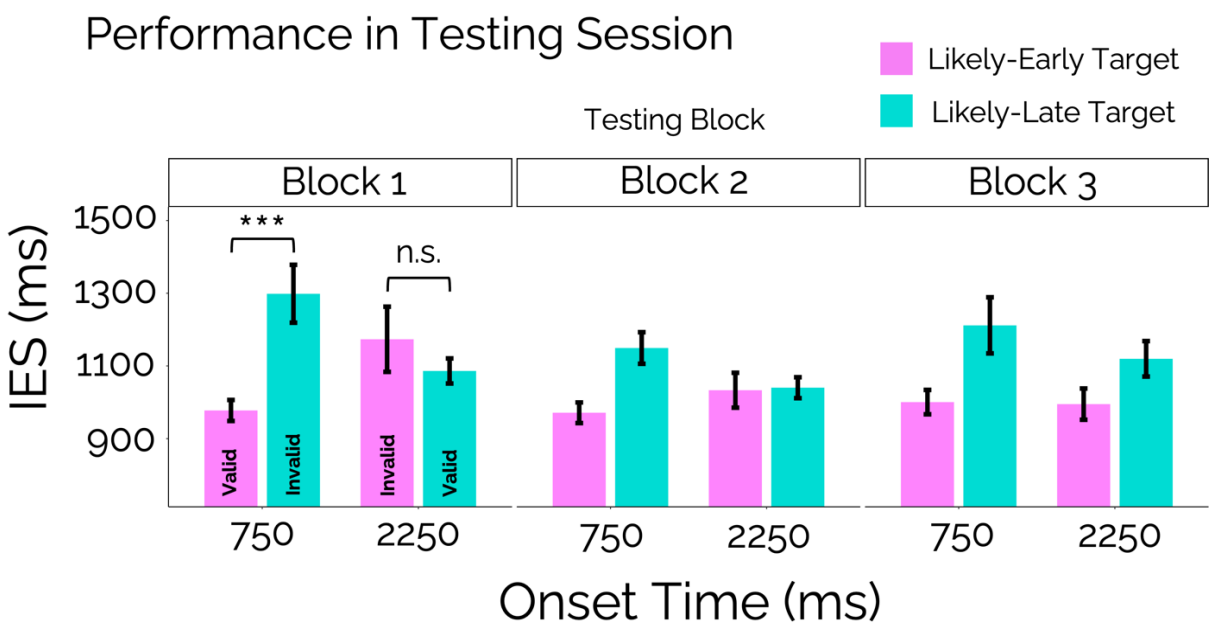


Figure 2.2. Mean (untransformed) IES values for identifying targets in each block of the testing session in Experiment 1, for likely-early and likely-late targets appearing at each onset time. Error bars represent ±1 standard error (*SE*) around the mean. The statistical significance of follow-up comparisons for Block 1 is indicated with asterisks: *** = $p < .001$, n.s. = not significant.

Learning Session: Fixation Likelihood Across Distractor Colours. When comparing fixation likelihood for distractors according to whether they shared their colour with a target, the optimal GLMM had a random-effects structure containing intercepts for individual participants and by-participant slopes for colour type (with both goal-dependent and prediction contrasts), block number, and their interaction. This model was specified in the syntax of R as:

Fixation ~ Colour Type * Onset Time * Block Number + (1 + Colour Type * Block Number | Participant)

The fixed effects output of this model is given in Table 2.3 below and visualised in Supplementary Figure 7.3.

Table 2.3

Experiment 1 Optimal GLMM Fixed Effects Output for Distractor Fixation Likelihood

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No Colour Match vs. Target Colour Match)	**-0.98**	**0.05**	**-20.34**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match)	**-0.22**	**0.09**	**-2.41**	**.016**
Onset Time	**0.09**	**0.02**	**5.45**	**< .001**
Block Number	**-0.08**	**0.03**	**-2.56**	**.010**
Goal-dependent Contrast (No Colour Match vs. Target Colour Match) : Onset Time	**0.05**	**0.02**	**2.57**	**.010**
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match) : Onset Time	0.03	0.05	0.66	.512
Goal-dependent Contrast (No Colour Match vs. Target Colour Match) : Block Number	**-0.08**	**0.02**	**-3.41**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match) : Block Number	0.02	0.05	0.30	.763

Predictor	β	*SE*	*z*	*p*
Onset Time : Block Number	0.01	0.02	0.68	.495
Goal-dependent Contrast (No Colour Match vs. Target Colour Match) : Onset Time : Block Number	-0.01	0.02	-0.44	.660
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match) : Onset Time : Block Number	0.01	0.05	0.30	.768

Goal-dependent Capture. The optimal GLMM provided evidence for goal-dependent attentional capture. Overall, the likelihood of fixating a distractor was significantly predicted by whether it shared its colour with any of the targets ($p < .001$). Overall, participants fixated significantly more on distractors of target colour ($M = 84.21\%$, $SD = 6.83\%$) than of non-target colour ($M = 56.88\%$, $SD = 6.83\%$; Figure 2.3B), consistent with attentional guidance toward target colours.

The GLMM also revealed a significant two-way interaction between the goal-dependent contrast and onset time ($p = .010$). When distractors onset early during trials, the mean difference in fixation rate between target-colour match distractors and no-match distractors was 29.51%. When distractors onset late, this mean difference was reduced to 24.84%. Here, early onset times are defined as between 250 ms and 1500 ms, and late onset times as between 1500 ms and 2750 ms. This finding of participants fixating more no-match distractors relative to target-colour match distractors when distractors appeared late is consistent with a reduction in goal-dependent attentional capture at later times during trials.

The two-way interaction between the goal-dependent contrast and block number was also significant ($p < .001$). The mean difference in fixation rates between target-colour match distractors and no-match distractors was 22.51% in the first block, compared to 31.50% in the final block. This is consistent with participants becoming more avoidant of fixating *no-match distractors* relative to target-match distractors, i.e., exhibiting greater goal-dependent attentional capture, as the learning session progressed.

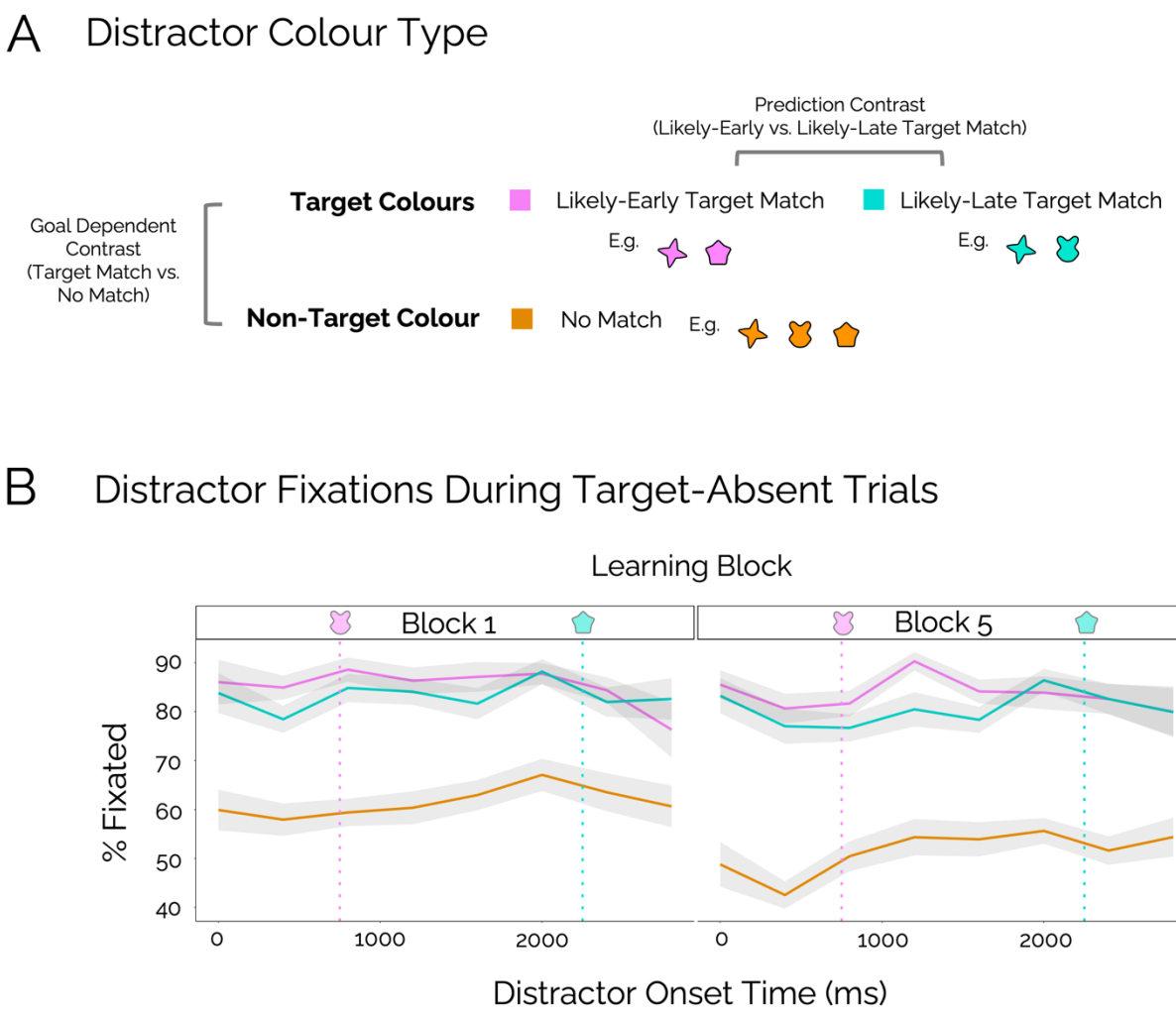


Figure 2.3. (A) Distractors matching the colour of the likely-early target, the likely-late target, or no target for the example targets from Figure 2.1C. The two different contrast comparisons for levels of colour type are also illustrated. **(B)** Percentage of distractors fixated in the first and last blocks of the learning session in Experiment 1, for each level of colour type, across onset times from 0 to 2750 ms. This plot only includes data from target-absent trials. Here, and in Figure 2.5, the dotted pink and blue lines indicate the expected onset times for the likely-early and likely-late target, respectively, illustrated using the example targets. The solid pink, blue, and orange lines represent mean values, while the grey shaded areas represent ±1 SE around the mean. For these visualisations only, data were smoothed by rounding onset times to the nearest 400 ms.

Feature-Temporal Capture. The GLMM did not provide significant evidence for temporally tuned capture according to the target colour predicted at early versus late onset times. The likelihood of fixating a distractor was, overall, significantly predicted by whether a distractor shared its colour

with the likely-early target *or* the likely-late target (prediction contrast; p = .016). Irrespective of onset time or block number, participants fixated significantly more distractors of likely-early target colour (M = 85.60%, SD = 4.06%) than of likely-late target colour (M = 82.80%, SD = 4.06%). Contrary to my hypothesis, the interactions between the prediction contrast and onset time (p = .512), and between the prediction contrast, onset time, and block number (p = .768; Figure 2.3B), were not significant. Therefore, despite clear evidence for temporally tuned behaviour during the testing session, I found no significant evidence that participants' preference to fixate likely-early target colour distractors over likely-late target colour distractors was temporally tuned to the task regularities, even as the learning session progressed.

2.4.3 Interim Discussion

The IES analysis for the first testing block found significant evidence that participants' performance was temporally tuned in line with the task regularities. Efficiency in identifying targets depended significantly on whether they appeared at their predicted (valid) or unpredicted (invalid) time. As hypothesised, target identification was more efficient when targets upheld, rather than violated, the feature-temporal regularities established during the preceding learning session. Further, this performance difference between feature-temporally valid and invalid targets was most pronounced, and only reached significance, when targets onset early during trials, as opposed to late.

In contrast, no evidence was found for temporal tuning of performance in the second and third testing blocks. This extinction of the temporal tuning effect suggests that, as the testing session progressed, participants relied less on temporal predictions about targets to guide behaviour. This decline may have resulted from increased exposure to temporally invalid targets across the testing session having weakened the strength or utility of participants' learned predictions. This rapid "unlearning" of feature temporal associations is interesting, particularly in contrast with long lasting regularity-based spatial biases (Britton & B. A. Anderson, 2020; Chun & Jiang, 2003; Jiang et al., 2013),

and feature-based biases (Lee & B. A. Anderson, 2023), found in the static search literature. Future work may wish to expand upon this discrepancy further to better understand the distinct mechanistic underpinnings of these processes.

The analysis of distractor fixations during target-absent trials in the learning session revealed strong evidence for goal-dependent attentional capture by target colours. This capture was found to be modulated by distractor onset time and learning block number, with distractors matching a target colour being fixated more often relative to no-match distractors both early during trials and during later blocks. This result suggests that our ability to filter task relevant from irrelevant features may be dynamic over time in trial and across experiment. These dynamics strongly support the need to consider search and attentional orienting across various timescales. However, importantly, overall, distractors matching a target colour were consistently more likely to be fixated than non-target-colour distractors, across all onset times and learning blocks (Supplementary Figure 7.2B). This suggests that participants consistently guided their attention toward target colours throughout the learning session.

Finding evidence for goal-dependent capture served as an important proof of concept that distractor fixations could reliably track participants' attentional priorities across stimulus colours in the DVS task. This justified using the same measure to test whether attention was further biased toward the colour of the *temporally likely* target. However, contrary to this hypothesis, no significant evidence was found for regularity-based temporal tuning of attentional capture to distractors of each target colour.

Instead, participants were consistently statistically more likely to fixate distractors matching the likely-early target colour than those matching the likely-late target colour. By the final learning block, this preference appeared more pronounced when distractors appeared in the first half of trials compared to the second half (Figure 2.3B, Block 5). However, ultimately, the tendency to fixate more

likely-early over likely-late target colour distractors did not interact significantly with distractor onset time or block number.

This apparent consistent attentional bias towards the likely-early target colour may have arisen for several reasons (see General Discussion). One possibility is that some participants struggled to form accurate temporal predictions during the busy DVS task, where intervals preceding targets were filled with unpredictable distractor appearances. While I found significant evidence of temporal tuning in participants' *performance*, greater noise in the fixations data, combined with variation between participants in the timing of prediction-based attentional shifts, may have obscured any corresponding effects on fixations. If this was the case, then increasing the interval between target onset times may help participants to form less noisy, or at least more distinct internal representations of each target's likely timing. If so, this may make it easier for participants to enact an effective shift in their feature-based attention at the appropriate time. I investigated this possibility in Experiment 2 , using a version of the DVS task with modified timings.

Another potential reason why temporal tuning effects were evident in performance, but not in fixations, is that performance reflected not just feature-based attentional processes but also motor response preparation. To additionally explore the temporal tuning of motor preparation, Experiment 2 used EMG recordings to investigate whether preparation was enhanced for temporally-predicted target responses.

2.5 Experiment 2

Participants in Experiment 2 completed a modified version of the DVS task used in Experiment 1. The main changes involved trial timings, the number of stimuli per trial, the number of learning and testing blocks, and the addition of EMG recording. These changes are detailed below.

2.5.1 Methods

Participants. The final sample consisted of 48 participants (35 female, one non-binary, 12 male; mean age = 22.85 ± 4.27 (*SD*)). Three additional participants were tested but their data were excluded for low accuracy. The final sample size was chosen a priori, partially because it is multiple of 12 to meet counter-balancing requirements. I increased the sample size from Experiment 1 to heighten the power for detecting EMG effects. Further, a *G*Power* analysis (G*Power 3.1; Faul et al., 2007) indicated that this sample size has a power of over 95% for detecting an effect of target likelihood on IES of size d = 0.75, as found in Experiment 1 (Testing Session, Block 1). This was calculated based on the use of a repeated-measures t-test with a significance criterion of .05 to analyse the effect.

Stimuli. During every DVS trial, exactly 14 stimuli appeared. Like in Experiment 1, zero, one, or two of these stimuli were targets. Each target appeared no more than once in a trial. Each distractor stimulus appeared at least once per trial, and, during trials where no targets appeared, each distractor appeared twice. On trials with one or both targets, six or five distractors, respectively, were randomly selected without replacement to appear a second time.

Trial Timings. All trials lasted 5500 ms. The early target onset time was 1000 ms and the late target onset time was 4000 ms. Participants had a window of 1500 ms following target onset to provide a correct response. The response window therefore lasted 750 ms after the target had disappeared. All distractor onset times fell between -650 ms and 5450 ms.

Procedure. After providing informed consent and demographic information, and before reading the DVS task instructions, participants were prepared for EMG recordings (see EMG Collection). Following practice, all participants completed a learning session of four blocks with 100% valid targets, followed by a testing session of just one block with 72% valid targets. Participants could

take breaks lasting up to three minutes between blocks. Experimental sessions lasted between 90 and 120 minutes.

EMG Collection. Muscle activity (EMG) was recorded with *SynAmps* amplifiers and *Neuroscan* data acquisition software (*Compumedics*). Two Ag-AgCl electrodes over the first dorsal interosseus muscle (FDI; between the index finger and thumb) recorded EMG in a bi-polar arrangement from each hand (see Figure 2.6A). The positive electrode was placed over the muscle belly and the negative electrode over the muscle tendon. A ground electrode was placed above the participant's left elbow (see Gagné & Schneider, 2008; Kleim et al., 2007; Kwon et al., 2016). Participants were instructed to respond with the left index finger on the 'F' key and right index finger on the 'J' key to ensure different hands were used to identify the likely-early and likely-late targets. Electrode impedance was aimed to be below 20 kΩ and was at least below 50 kΩ. Supplementary Figure 7.9 shows the strong EMG signals recorded during learning-session trials during which two targets appeared, each requiring a unique response. The relevant analysis focused on changes in EMG muscle excitability in target-absent trials.

Variables of Interest for Learning Session: Temporally Tuned Response Activity. In addition to investigating how learning the task regularities influenced participants' performance and attentional capture to target features, I also investigated whether motor activity related to each target response became temporally tuned.

This analysis used EMG recordings from both hands during target-absent trials from the learning session. Specifically, I tested whether differences in muscle activity between the hands varied systematically over the trial duration depending on which target was temporally likely. The dependent variable was the activity in the FDI muscles recorded using EMG. The independent variables were the response hand associated with each target ('target response hand': likely-early or likely-late) and learning block number (one to four). I additionally considered "time in trial" as

measured from the beginning of each trial in ms. Unlike the distractor fixations analysis, in which I investigated changes across *distractor onset times*, the EMG analysis tested for motor-excitability differences across *absolute time in trial*. This is because, unlike the fixation measure, EMG recordings were not locked to any stimulus appearance.

The analysis tested whether the difference in activity between the two hands was significant at different time points during trials, across learning blocks. I hypothesised that, if motor preparation was tuned according to the task regularities, then I would find significantly greater activity in the likely-early target response hand near its anticipated onset time of 1000 ms. Similarly, I would find greater activity in the likely-late target response hand around 4000 ms. This pattern should be most pronounced during later learning blocks, after participants had greater opportunity to learn the task regularities.

This analysis was restricted to target-absent trials from the learning session to avoid conflating any effects of temporal predictions with effects due to target appearances. All EMG signals were analysed, including those that may have corresponded to a false alarm. However, false alarm rates were low, with participants false alarming on 4.29% of target-absent learning session trials on average.

Statistical Analysis. ***Data Cleaning.*** Cleaning of RT data removed 0.67% of data from the learning session and 0.71% of data from the testing session.

EMG Preprocessing. Forty-six of the 48 participants had useable EMG data. All EMG preprocessing was conducted in MNE-Python (Gramfort, 2013). Data were notch filtered at 50 Hz to remove line noise during recording and later high-pass filtered offline at 20 Hz. On the participant level, I re-coded data from each hand as coming from the 'likely-early' or 'likely-late' target response hand, according to whether they used the 'F' or 'J' key to identify each target. EMG signals were rectified and normalised, within each hand, and within each trial, per participant.

Testing Session: Behavioural Performance. I analysed the IES values from the testing session using a 2x2 (onset time x target likelihood) repeated-measures ANOVA test. For completion, supplementary analyses assessed the effects of target likelihood and onset time on hits and RT individually. Results of these supplementary analyses are visualised in Supplementary Figure 7.5 and provided in Supplementary Table 7.6 and Supplementary Table 7.7.

Learning Session: Response Hand Activity. Each participant's EMG data were averaged and then smoothed separately for each learning block. Smoothing was carried out using the *gaussian_filter1d* function from the SciPy library (Virtanen et al., 2020) across a 70-ms window. I tested for significant differences in activity between hands, over time in trial, and over learning blocks, by employing the *clusterlm* function from the *permuco* package in R (Frossard & Renaud, 2021). I used a significance level of 5% and ran 5000 permutations. Block number entered the model as a continuous variable, centred and scaled. The model allowed for the difference between hands to interact with block number.

2.5.2 Results

Testing Session: Performance Benefits for Feature-Temporally Predictable Targets. In line with *boxcox* recommendations, IES values underwent a reciprocal transformation prior to analysis. The ANOVA revealed a significant main effect of target likelihood (p = .019). Overall, participants were more efficient at identifying the likely-early target (M_{IES} = 1163 ms, SD_{IES} = 309 ms) than the likely-late target (M_{IES} = 1264 ms, SD_{IES} = 309 ms). Of greater interest, the ANOVA also revealed a significant two-way interaction between target likelihood and onset time (p = .006; Figure 2.4). All other predictors were non-significant. Table 2.4 contains the full ANOVA output.

Two follow-up repeated-measures t-tests analysed the effect of target likelihood for each onset time. When targets onset at 1000 ms, target likelihood significantly affected IES, $t(47) = 3.56$, $p < .001$, $d = 0.46$, $BF_{10} = 33.13$. As hypothesised, participants were more efficient at identifying the

temporally valid likely-early target (M_{IES} = 1114 ms, SD_{IES} = 371 ms) than the temporally invalid likely-late target (M_{IES} = 1355 ms, SD_{IES} = 371 ms; Figure 2.4). In contrast, when targets onset at 4000 ms, target likelihood had no significant effect on IES, $t(47) = 0.37$, $p = .712$, $d = 0.07$, $BF_{10} = 0.17$.

Table 2.4

Experiment 2 Testing Session IES Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	1.99	1	47	.165	.004
Target Likelihood	**5.92**	**1**	**47**	**.019**	**.038**
Onset Time : Target Likelihood	**8.35**	**1**	**47**	**.006**	**.026**

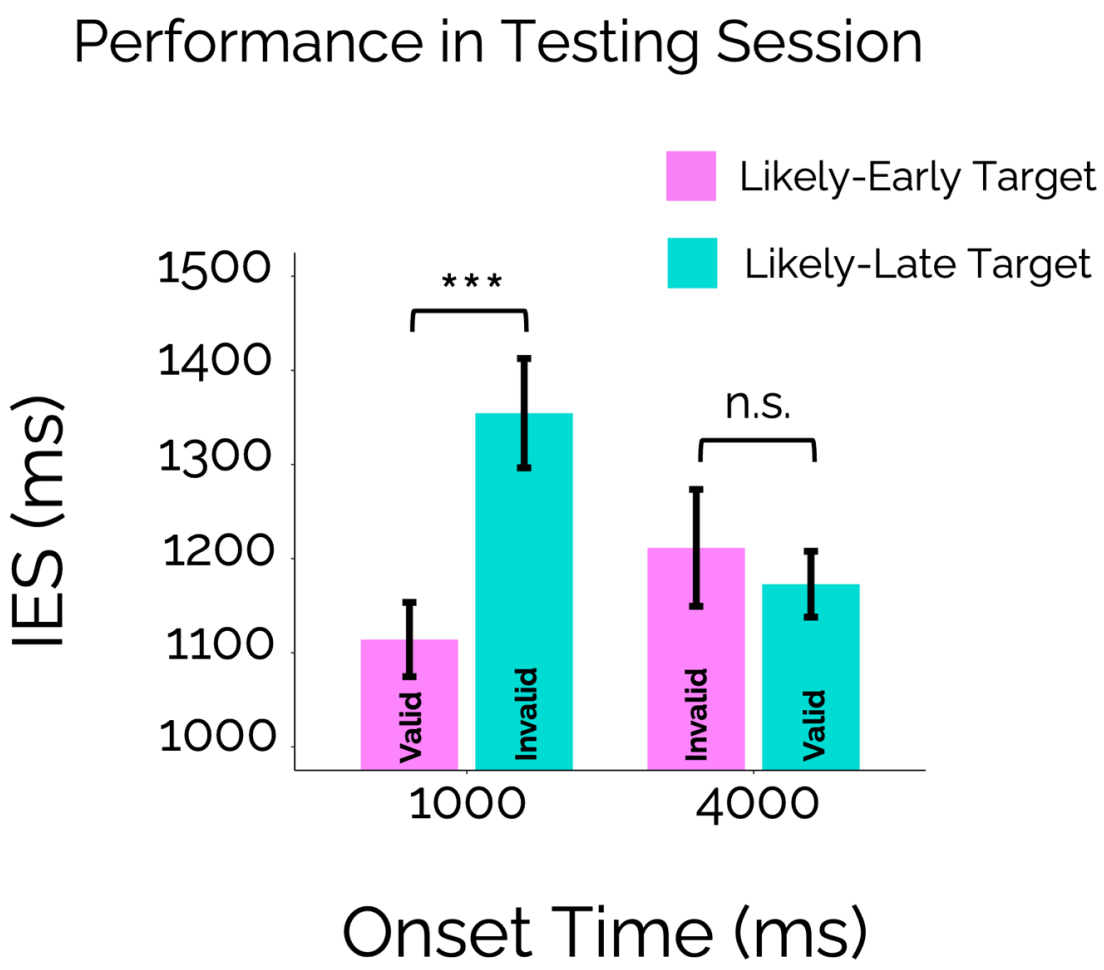


Figure 2.4. Mean (untransformed) IES values for identifying targets in the testing block in Experiment 2, for likely-early and likely-late targets appearing at each onset time. Error bars represent ±1 standard error (SE) around the mean. The statistical significance of comparisons is indicated with asterisks: *** = $p < .001$, n.s. = not significant.

Learning Session: Fixation Likelihood Across Distractor Colours. When comparing fixation likelihood for distractors according to their colour type, the optimal GLMM had a random-effects structure containing intercepts for individual participants and by-participant slopes for colour type (with both goal-dependent and prediction contrasts), block number, and their interaction. This model was specified in the syntax of R as:

Fixation ~ Colour Type * Onset Time * Block Number + (1 + Colour Type * Block Number | Participant)

The fixed-effects output is given in Table 2.5 and visualised in Supplementary Figure 7.7.

Table 2.5

Experiment 2 Optimal GLMM Fixed Effects Output for Distractor Fixation Likelihood

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No Colour Match vs. Target Colour Match)	**-0.86**	**0.05**	**-17.26**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match)	-0.03	0.07	-0.51	.608
Onset Time	**0.03**	**0.01**	**2.97**	**.003**
Block Number	**-0.09**	**0.03**	**-3.36**	**< .001**
Goal-dependent Contrast (No Colour Match vs. Target Colour Match) : Onset Time	0.01	0.01	-0.03	.973
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match) : Onset Time	**0.07**	**0.03**	**2.50**	**.012**
Goal-dependent Contrast (No Colour Match vs. Target Colour Match) : Block Number	**-0.05**	**0.02**	**-3.03**	**.002**

Predictor	β	*SE*	*z*	*p*
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match) : Block Number	-0.01	0.04	-0.14	.887
Onset Time : Block Number	0.01	0.01	0.99	.322
Goal-dependent Contrast (No Colour Match vs. Target Colour Match) : Onset Time : Block Number	-0.01	0.01	-1.10	.270
Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match) : Onset Time : Block Number	**0.08**	**0.03**	**2.98**	**.003**

Goal-Dependent Capture. Like in Experiment 1, the GLMM provided evidence for goal-dependent capture. Overall, the likelihood of fixating a distractor was significantly predicted by whether it shared its colour with a target ($p < .001$). Consistent with attentional guidance toward target colours, participants fixated significantly more distractors of target colour (M = 72.72%, SD = 7.53%) than of non-target colour (M = 46.09%, SD = 7.53%; Figure 2.5).

The two-way interaction between the goal-dependent contrast and learning block number was also significant (p = .002). The difference between the fixation rate for target colour match vs. no colour match distractors was 23.62% in the first learning block, compared to 30.02%. in the last block. This is consistent with participants becoming more avoidant of fixating no-match distractors, relative to target-match distractors, throughout the learning session. In contrast to Experiment 1, the goal-dependent contrast did not interact significantly with distractor onset time (p = .973).

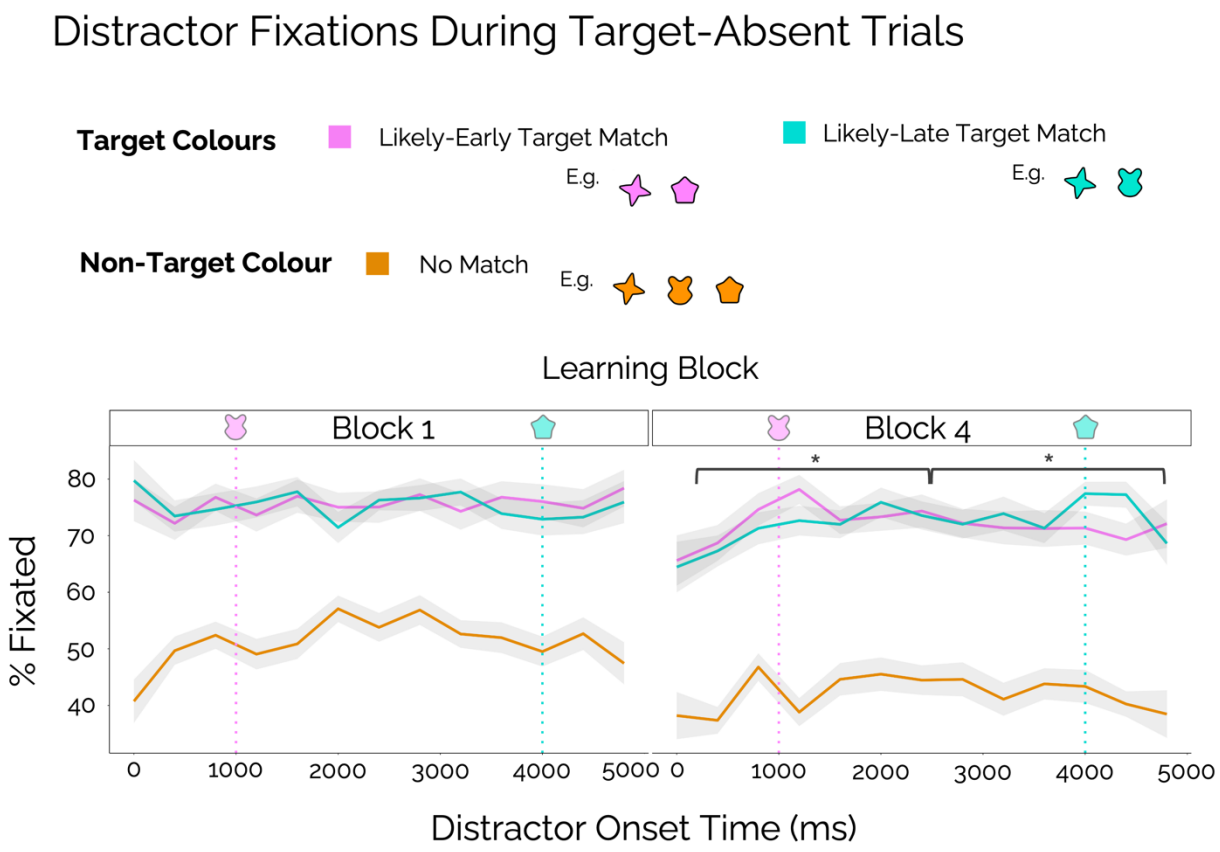


Figure 2.5. Percentage of distractors fixated in the first and last blocks of the learning session in Experiment 2, for each level of colour type, across onset times from 0 to 4750 ms. This plot only includes data from target-absent trials. The statistical significance of comparisons between likely-early and likely-late target match distractors in Block 4 is indicated with an asterisk where * = $p < .05$.

Feature-Temporal Capture. In contrast to Experiment 1, Experiment 2 also provided evidence for temporally tuned attentional capture, according to the colour of the target predicted to onset at the early vs late time. Overall, the likelihood of fixating a distractor was not significantly predicted by whether it shared its colour with either the likely-early target *or* the likely-late target ($p = .608$). However, importantly, the two-way interaction between the prediction contrast (likely-early vs. likely-late target colour match) and onset time was significant ($p = .012$). This implies that the likelihood of participants fixating distractors of each target colour varied depending on onset time. Further, a significant three-way interaction between the prediction contrast, onset time, and block

number revealed that the extent of this temporal tuning changed significantly across the learning session (p = .003).

To interpret this significant three-way interaction, two additional GLMMs assessed the significance of the two-way interaction between the prediction contrast and onset time separately for the first and last block of the learning session. Both optimal GLMMs had random-effects structures containing intercepts for individual participants and by-participant slopes for colour type:

Fixation ~ Colour Type * Onset Time + (1 + Colour Type | Participant)

For the first learning block, the interaction between the prediction contrast and onset time was not significant (β = -0.08, SE = 0.06, z = -1.36, p = .174; Figure 2.5). In line with my hypothesis, this interaction *was* significant for the final learning block (β = 0.15, SE = 0.06, z = 2.71, p = .007; Figure 2.5).

To interpret this significant two-way interaction, I ran two further GLMMs analysing the effect of the prediction contrast during learning block four, for distractors with 'early' or 'late' onset times. Early onset times were defined as those between 250 and 2500 ms, and late onset times as those between 2500 and 4750 ms. Both optimal GLMMs had random-effects structures containing intercepts for individual participants and by-participant slopes for colour type:

Fixation ~ Colour Type + (1 + Colour Type | Participant)

In learning block four, distractors that appeared early during a trial were significantly more likely to be fixated if their colour matched the likely-early target (M = 74.28%, SD = 10.00%), rather than the likely-late target (M = 70.74%, SD = 8.20%; β = -0.24, SE = 0.10, z = -2.37, p = .018). In

contrast, for distractors that appeared late, those matching the likely-late target colour (M = 73.75%, SD = 8.74%) were significantly more likely to be fixated than those matching the likely-early target colour (M = 70.93%, SD = 9.26%; β = 0.21, SE = 0.10, z = 2.04, p = .042). Overall, by the final learning block, participants demonstrated a preference to fixate distractors sharing colour with likely-early targets at the beginning of trials and with likely-late targets toward the end of trials (Figure 2.5, Block 4).

Learning Session: Temporally Tuned Response Hand Activity. EMG recordings revealed temporally specific heightened motor response activity for the response associated with the likely-early target. Regarding the difference in activity between hands, the analysis revealed a significant cluster for which the difference peaked at 1466 ms (p = .027). Here, participants had significantly greater activity in their likely-early target hand than their likely-late target hand, with the peak difference aligning temporally with the anticipated likely-early target appearance (Figure 2.6B). A second cluster, corresponding to a later time-in-trial was also revealed (time of peak difference 4721 ms; p = .578). Here, the average activity in the likely-late target hand was greater than that in the likely-early target hand, though this difference was ultimately not significant.

No significant clusters were found as a function of block number, or the interaction between block number and target response hand.

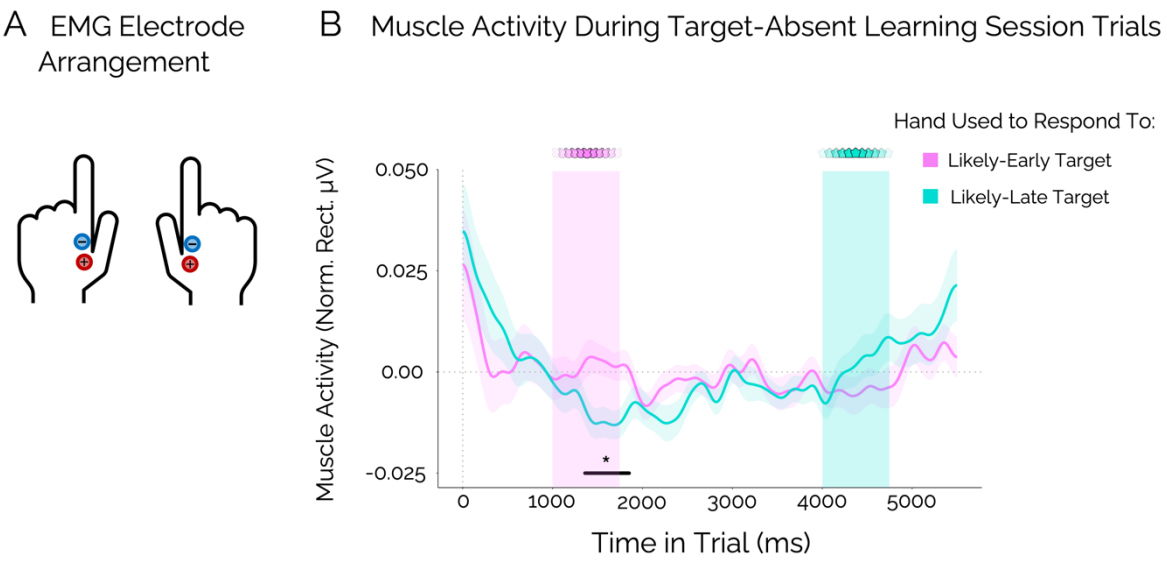


Figure 2.6. (A) Illustration of the positive and negative EMG electrode arrangements over the FDI muscle in each hand. **(B)** Normalised rectified muscle activity in hands responding to the likely-early and likely-late targets across the 5500 ms duration of target-absent learning session trials in Experiment 2. The solid pink and blue lines represent the mean values and the shaded areas around them represent ±1 SE. The pink and blue columns indicate the time windows over which the likely-early and likely-late target, respectively, would have faded in and out, if they had appeared. The black horizontal line marks a significant cluster where * = $p < .05$.

2.5.3 Interim Discussion

Consistent with findings for the first testing block in Experiment 1, the IES analysis revealed that target identification efficiency depended significantly on whether targets appeared at their predicted (valid) or unpredicted (invalid) time. As hypothesised, performance was more efficient when target timings matched those from the preceding learning session. These benefits of temporal validity reached significance only when targets appeared early during trials, not late. As in Experiment 1, participants were able to learn and use the feature-temporal regularities in the DVS task to dynamically guide their behaviour throughout trials. Importantly, I replicated this pattern of results from Experiment 1 using different target onset times and fewer learning trials, allowing us to further generalise with regards to the robustness of the feature-temporal behavioural guidance.

Also consistent with Experiment 1, the distractor fixation analysis revealed strong evidence of goal-dependent attentional capture by target colours. This effect was again modulated by block number. Target-colour distractors were again fixated more relative to non-target-colour distractors in all learning blocks, but to a greater extent during later blocks (Supplementary Figure 7.7B). This strong and consistent evidence for goal-dependent capture across experiments highlights the reliability of distractor fixations as a proxy measure of feature-based attentional guidance in the DVS task. Unlike in Experiment 1, however, the magnitude of goal-dependent capture did not vary significantly with distractor onset time, suggesting that attention was biased toward target colours to a similar extent throughout trials.

In contrast to Experiment 1, the fixations analysis in Experiment 2 revealed that, by the end of the learning session, relative attentional capture to each target colour was temporally tuned to the regularities in target timing. Overall, there was no significant difference between participants' likelihood to fixate distractors matching each target colour when onset time was not considered, suggesting both target colours captured attention to a similar extent. However, when onset time was taken into account, relative capture to each target colour varied significantly over onset times in the final learning block. Specifically, for distractors appearing at both early and late times during trials, those matching the colour of the temporally likely target (i.e., the likely-early or likely-late target, respectively) were significantly more likely to be fixated than those matching the temporally-unlikely-target colour, as hypothesised. As such, the performance benefits for temporally valid targets in the testing session were likely (partly) driven by enhanced attentional guidance toward temporally expected target colours here.

EMG results from target-absent learning-session trials also found evidence for temporal tuning of participants' behaviour aligned with the task regularities. The finding suggests that enhanced motor preparation for the temporally predicted target response also likely contributed to

the performance benefits for temporally valid targets in the testing session. Muscle activity was significantly greater in the hand associated with the likely-early target, relative to the hand associated with the likely-late target, selectively around the anticipated appearance time of the likely-early target. No significant difference in muscle activity between hands was observed at later times during trials. Unlike temporal tuning of feature-based attentional capture, temporal tuning of motor activity did not increase significantly over learning blocks, suggesting it may have been quickly established and may operate across a different timescale than visual attentional guidance.

2.6 General Discussion

The work in this chapter demonstrates that learned feature-temporal predictions can adaptively guide visual search behaviour over time. Converging behavioural data from both experiments, and eye-tracking and EMG data from Experiment 2, revealed temporal tuning of participants' task performance, feature-based attentional capture, and motor activity in line with task regularities. Extending prior research on dynamic visual search (Boettcher et al., 2022; Shalev et al., 2022, 2024; Xu et al., 2023), these findings highlight the flexibility of temporal attention to modulate search behaviour even under spatial uncertainty. Moreover, the novel task design advances previous work on feature-temporal attention (Echeverria-Altuna et al., 2024; Gao et al., 2025; Thomaschke et al., 2016; Wagener & Hoffmann, 2010) by demonstrating selective feature-temporal attentional guidance impacting sensory selection and motor preparation to identify and respond to targets appearing among competing distractors in a free-viewing dynamic visual search task.

In both experiments, participants identified temporally valid targets significantly more efficiently than temporally invalid targets in the first testing block. This is consistent with participants having learned the feature-temporal regularities in the preceding learning session and used them to guide behaviour. As I only analysed one-target trials, the observed differences in performance for the

likely-early and likely-late targets between early and late onset times cannot not be attributed to a change in strategy following the detection of a target at the early time. Instead, these shifts are likely the result of participants tracking time within the trial and shifting their internal templates accordingly.

Interestingly, performance differences between feature-temporally valid and invalid targets in both experiments were most pronounced when targets appeared early. This aligns with previous studies investigating temporal expectations based either on informative temporal cues (Coull et al., 2000; Heideman et al., 2018) or on learnt regularities (Xu et al., 2023, 2025), which found a significantly larger effect following a short, but not long interval. Future research should explore why temporal expectations may guide behaviour more effectively at shorter intervals. Factors to consider include differences in estimating short and long intervals, difficulties enacting shifts in attentional or motor processes away from initial prioritisations, or ceiling effects at later times due to proactive guidance of temporal expectations to the later time point based on internal monitoring of the known trial duration.

In contrast, Boettcher et al. (2022) and Echeverria-Altuna et al., (2024) reported significant performance benefits for temporally expected target locations and features, respectively, occurring at both early and late times during trials. A possible explanation for these differences is that, in the present studies, I analysed performance for late targets that were not preceded by another target. For Boettcher et al., (2022), and Echeverria-Altuna et al., (2024), temporally expected late targets were always, or mostly, preceded by an earlier temporally expected target in the same trial. It is possible that these extra temporally predictable targets helped participants to encode temporal regularities at later times by providing additional reliable reference points after trials had begun and engendering more distinct representations of the early versus late target timings (Bangert et al., 2020; Ongchoco et al., 2023). Further investigation is needed to explore why effects of temporal

predictions may be weighted toward early time points in some contexts and not others, and whether the formation of temporal predictions at later intervals is hindered in environments with fewer reliable temporal anchors.

Going beyond traditional performance metrics, I used eye tracking to probe feature-based capture of attention throughout trials, even in the absence of target appearances. Participants in both experiments were overall more likely to fixate distractors that shared their colour with one of the targets compared to those that did not share their colour with any target. This demonstrated that my measure of distractor fixations could reliably track participants' internal attentional priorities.

Experiments 1 and 2 differed in whether they found evidence of dynamic, within-trial tuning of attentional capture toward the temporally likely target colour. In Experiment 1, participants consistently fixated more likely-early-target colour distractors than likely-late-target colour distractors. This preference did not vary significantly across distractor onset times. In contrast, by the end of the learning session in Experiment 2, participants' preference to fixate likely-early-target colour distractors was selective to distractors that had appeared early during trials. For distractors that had appeared late, those of likely-late-target colour were instead fixated most often. Therefore, while this evidence suggests attentional guidance to target colours was not temporally tuned in Experiment 1, the Experiment 2 results suggest participants adapted their attentional priorities over time during trials, in line with the task regularities. Importantly, because this analysis focused on target-absent trials, the observed mid-trial switch in attentional priorities in Experiment 2 cannot be explained by participants simply starting to look for a different target to that which they found early in the trial. Instead, the results point to truly dynamic temporally-contingent feature-based attentional guidance.

While it is not possible to determine why exactly the experiments differed in their findings on regularity-based attentional guidance, it is plausible that the longer interval between target onset

times in Experiment 2 helped participants form more accurate predictions and/or to use them more effectively to shift their attention to a measurable extent at an appropriate time. Although, it is notable that the performance benefits for temporally likely targets were present in both Experiment 1 and 2. Future studies could investigate the conditions under which feature-temporal regularities are most likely to be learned and effectively used to guide visual attention specifically in busy, dynamic environments.

The distractor fixation results from Experiment 2 complement previous work demonstrating anticipatory eye movements toward temporally likely target locations, rather than features, following learning of spatiotemporal regularities (Boettcher et al., 2022; Pfeuffer et al., 2020). One mechanism by which spatiotemporal regularities may benefit behaviour is temporally tuned ocular motor planning. It is not possible to determine the extent to which the results of the aforementioned studies reflect underlying shifts in spatial attention or saccade preparation. In contrast, the present experiments investigated eye movements in a context where all stimuli appeared with large spatial uncertainty. As such, the findings of Experiment 2 are unlikely to reflect the temporal preparation of directional saccades. Instead, the gaze results expose more directly dynamically tuned shifts in feature-based attention.

My findings of temporal expectations modulating selective attentional guidance in Experiment 2 even under large spatial uncertainty extend previous research on temporal attention. They demonstrate that temporal predictions serve to modulate not only where, but also *what* receives attentional priority. Modulation by temporal expectation occurs even when spatial locations are highly unpredictable, beyond just one or two possible locations (Echeverria-Altuna et al., 2024; Gao et al., 2025; Thomaschke et al., 2016; Wagener & Hoffmann, 2010). This furthers the argument that, while spatial certainty may aid the operation of temporal attention, it is not always necessary.

While all of the measures in Experiment 2 revealed behavioural shifts according to the task regularities, the eye-tracking results differed from the performance and EMG results in one key respect. Gaze modulation pointed to significantly greater attentional capture for the temporally-valid-target colour compared to the temporally-invalid-target colour at both early and late times during trials. Therefore, while I did not find evidence for enhanced performance or muscle activity associated with the temporally valid target at late times during trials, I did find evidence for enhanced attention to the temporally valid target colour. Further research may explore whether the effects of temporal predictions on earlier stages of target selection, as indexed by the gaze effects, differ in nature from those at later, motor-related processes.

Beyond my primary focus on effects of feature-temporal expectations, the eye-tracking analysis revealed a striking effect of general task goals on attentional capture. Across both experiments, participants overwhelmingly fixated more distractors that matched a target colour than those that did not, regardless of onset time or block number. This preference increased as participants gained task experience. As stimuli appeared across a wide range of unpredictable spatial locations, this supports evidence that goal-driven feature-based attention operates effectively across spatially unattended locations (Brignani et al., 2010; Saenz et al., 2002; Treue & Trujillo, 1999). Additionally, I observed these strong feature-based contingent capture effects in an extended dynamic setting where all stimuli appeared at different times. It is not necessarily intuitive that I would have detected these effects over and above any capture effects due to abrupt stimulus onsets (Schreij et al., 2008, 2010).

While this chapter primarily examined colour-based attentional guidance, future research could explore visual attentional guidance toward other features in dynamic contexts and whether they may be temporally tuned. I found that target shapes did not substantially guide attention in the DVS tasks, nor was guidance toward shapes temporally tuned (see Supplementary Figure 7.4 and

Supplementary Figure 7.8). This is perhaps unsurprising, given the dominance of colour in guiding attention compared to shapes (Alexander et al., 2019; Wolfe & Horowitz, 2017). However, it is possible that shape-based attentional guidance may be temporally tuned in a task where shape is the primary basis for guidance. DVS tasks may also provide insights into attentional guidance to dynamic stimulus features, such as motion (Boettcher & Nobre, 2025) or systematically changing colours (Muhl-Richardson, Cornes, et al., 2018; Muhl-Richardson, Godwin, et al., 2018). While the current findings suggest that temporal predictions can shift attentional priorities between internal representations of a static target feature (colour), it would be interesting to consider if the same is true for representations of dynamic features.

In addition to performance and eye tracking metrics, the EMG results from Experiment 2 are consistent with regularity-based temporal tuning of participant behaviour. Early during trials, significantly greater muscle activity was found in the hand associated with the temporally expected target response than in that associated with the temporally unexpected target response. These findings complement Volberg & Thomaschke's (2017) findings of temporally tuned effector-specific preparatory brain activity in a task where target stimuli and their associated responses varied predictably with the duration of the foreperiod preceding the target.

In the DVS tasks used in this chapter, specific motor responses were inherently tied to the feature-temporal regularities, which may have reinforced participants' learning. Temporal predictions strongly modulate motor preparation (Rolke & Ulrich, 2010; Thomaschke et al., 2011; Volberg & Thomaschke, 2017), and coupling of motor actions to temporally predictable events enhances perceptual modulations (Coull et al., 2024). Future research should confirm whether temporally predictable motor responses are necessary for temporal regularities to be learned and to benefit behaviour, as has been suggested by some researchers (e.g., Salet et al., 2022; Thomaschke & Dreisbach, 2013). Chapter 3 aims to extend our understanding by investigating the benefits of

feature-temporal regularities on performance, both in insolation and in combination with motor-temporal regularities.

Future research could further explore different combinations of temporally contingent location-, feature- and action-based regularities to better understand how they interact to enhance search efficiency. It would be valuable to determine whether, when concurrent, these regularities provide additive benefits, if one is dominant and required, or if certain interactions are particularly strong. Additionally, it would be informative to investigate whether temporal predictability alone can guide dynamic visual search behaviour, without co-occurrence with another sensory-motor prediction.

Looking forward, my DVS task and eye-tracking approach offer a promising method for further investigation of feature-temporal attentional guidance throughout dynamic visual search. For example, this framework could be used to better understand how temporal regularities operating at different timescales influence behaviour; from more local intervals between successive stimuli, to regularities occurring across trials.

Finally, future work should examine the paths via which predictable timing can enhance search performance by dynamically modulating attentional control. While this chapter focused on improvements driven by increased attentional capture by temporally expected target features, it remains unclear whether similar performance benefits could arise from dynamic suppression of temporally likely *distractor* features. This is an intuitive possibility, as dynamic suppression has been demonstrated for salient distractors appearing at predictable times (Lamy, 2005) and at temporally likely locations (Xu et al., 2021). Chapter 4 uses another dynamic task to investigate the existence of adaptive feature-temporal attentional suppression.

2.7 Conclusion

Using a novel experimental task design, I provide initial evidence for adaptive, temporally tuned shifts of feature-based attentional guidance during free-viewing dynamic visual search. I found that learning of temporally contingent regularities during search can affect task performance, attentional capture by target features, and motor response activity in a temporally specific way. This work underscores the flexibility of our attentional system and the utility of temporal predictions in modulating attentional guidance, even under large spatial uncertainty and in crowded dynamic environments.

3 Distinct Benefits of Feature- and Motor-Temporal Target Regularities

3.1 Abstract

In lab-based and real-world settings, visual search tasks often involve coordinating perceptual and motor systems. Given the close relationship between timing and motor preparation, it is important to consider how temporal predictions affect action, as well as perception, during dynamic visual search (DVS). Chapter 2 revealed performance benefits for targets with temporally likely, versus unlikely, non-spatial features and responses in a DVS task. The present chapter builds upon these initial findings. I used an online DVS task to investigate whether 1) performance benefits for feature-motor-temporally predictable targets could be replicated, 2) these effects reflect benefits relative to a neutral baseline or a cost of processing unexpected information, and 3) similar benefits emerge for targets that are either feature-temporally *or* motor-temporally predictable, but not both. Each target appeared in pink or blue, required a left or right response, and appeared early or late during a trial. Unlike in Chapter 2, colour and response were disentangled, allowing the temporal predictability of each to be manipulated independently in four between-subjects conditions. The temporally predictable target property(ies) varied by condition: colour in the 'feature-temporal' (FT) condition, response in the 'motor-temporal' (MT) condition, both colour and response in the 'feature-motor-temporal' (FMT) condition, and neither in the 'neutral' (N) condition. During an initial learning session, targets always followed assigned regularities. In a subsequent testing session, regularities were occasionally violated. Comparisons of performance between conditions in the learning session revealed some time-sensitive benefits for each of the FT, MT, and FMT conditions over the N condition, suggesting that each regularity benefitted target identification to some degree. To further

investigate regularity-based behavioural tuning in these conditions, I tested for performance benefits for temporally likely versus unlikely targets in the testing session. Despite suggestive trends in the data, no significant benefits emerged in any condition. Overall, these mixed findings indicate that, while feature-temporal predictions may still benefit DVS under both spatial *and* motor uncertainty, this warrants further investigation. In addition, differences from the findings in Chapter 2 highlight the sensitivity of temporal prediction effects to variations in task design. More broadly, this chapter emphasises the need to consider how temporal predictions may distinctly affect both visual attention and response processes during DVS.

3.2 Introduction

Visual search tasks are widely used to study selective attention, yet successful target identification often involves additional cognitive processes. For example, in everyday life, visually locating a goal-defined target is often accompanied by a goal-based action, such as when finding and picking up your phone from a cluttered desk. Despite this, motor processes during visual search are rarely examined. Traditional, static search paradigms assume motor execution times are constant, and response time (RT) differences are attributed to visual processes of interest (McGill, 1963; Palmer et al., 2011).

Recent studies investigating visual search in *dynamic* environments are faced with more complex motor effects, particularly when investigating temporal predictions (e.g., Boettcher et al., 2022; Shalev et al., 2022, 2024; Xu et al., 2021, 2023). In dynamic real-world settings, goal-directed actions depend on predicting not just *where* but also *when* to act (De Kock et al., 2021). For example, catching a ball requires accurate temporal and spatial predictions. In static search tasks, temporal predictions are less relevant for action preparation, as motor timing is primarily determined by the preceding visual and decision-making processes initiated at display onset. By contrast, in dynamic

tasks, the evolution of visual information during trials allows predictions about *when* targets will appear to influence motor preparation more directly. Therefore, to understand how temporal predictions influence behaviour during dynamic visual search (DVS), it is essential to examine their effects on motor preparation, both independently of, and together with, visual attention.

In Chapter 2, I found that, when both non-spatial target features *and* target responses were simultaneously temporally predictable in a DVS task, participants modulated their performance (Experiments 1 & 2), feature-based attention (Experiment 2), and motor activity (Experiment 2) based on the temporally likely target. In those tasks, and in a related study reporting similar performance benefits for feature-temporally likely versus unlikely targets (Wagener & Hoffmann, 2010), target features were inherently liked to motor responses, meaning regularities were truly feature-*motor*-temporal. This makes it unclear whether the observed performance benefits were driven by temporal predictions about target features, target responses, or both. The present chapter aims to disentangle these components by examining the individual effects of feature-temporal and motor-temporal target predictability on DVS performance, and by investigating whether each can operate independently of the other. Here, I hope to shed light on a few open questions regarding performance benefits during dynamic visual search: 1) whether motor-temporal regularities that are decoupled from defining sensory features confer a temporal orienting benefit and 2) whether temporal predictions combined with feature regularities, in the absence of effector response preparation, can still lead to performance benefits.

Consider first the case where targets in a DVS task are temporally predictable in terms of response, but not features. In this scenario, it seems likely that performance benefits may still emerge for identifying temporally likely versus unlikely targets. In general, temporal expectations are well established to speed responses and modulate preparatory motor activity (Correa et al., 2006; Nobre, 2001; Rolke & Ulrich, 2010; Salet, Kruijne, van Rijn, et al., 2022; Thomaschke et al., 2011; Thomaschke

& Dreisbach, 2013; Ullén & Bengtsson, 2003; van Ede et al., 2020; Volberg & Thomaschke, 2017). Although this suggests that participants could plausibly learn and use motor-temporal regularities even when upcoming target features are uncertain, this has yet to be definitively shown during DVS.

Now consider that DVS targets are temporally predictable in terms of feature, but not response. Whether these isolated temporal regularities would result in observable performance benefits is unclear. Some studies have found specifically that, while temporal regularities linked to response effectors enhance performance, those linked to target locations or features do not (Salet, Kruijne, Rijn, et al., 2022; Thomaschke et al., 2011, but see also: Doherty et al., 2005; Rohenkohl et al., 2014). Additionally, temporal preparation has historically been thought to primarily enhance late-stage processing (e.g., response selection and execution), rather than earlier perceptual or attentional stages (e.g., Coull et al., 2000; Näätänen, 1971; for reviews see Rolke & Ulrich, 2010; Seibold et al., 2023). It is therefore less clear whether feature-temporal target predictability would result in performance benefits in the absence of motor-temporal regularities.

In Chapter 2 (Experiment 2), I did find changes in my measure of feature-based attention that were dynamically tuned to the task regularities. This suggests that performance benefits for temporally likely targets were not solely due to enhanced response readiness, but also reflected adaptive attentional guidance. Notably, this tuning occurred in target-*absent* trials where no responses were required. This suggests that time-locked motor actions are not strictly necessary for learnt temporal predictions to modulate feature-based attention, though effects due to motor *preparation* cannot be ruled out. That said, perceptual systems in the brain are not as strongly implicated in predictive timing as motor areas (Cotti et al., 2011; Coull et al., 2000, 2024; Coull & Nobre, 1998; Griffin et al., 2001). Moreover, coupling motor responses to perceptual events has been shown to enhance the precision of temporal predictions about those events, and to modulate attention more effectively over time in sensory domains (Coull et al., 2024; Morillon et al., 2014;

Morillon & Baillet, 2017). Therefore, it remains possible that the temporal modulation of participants' feature-based attention in Chapter 2 could only be established in the first place due to the scaffolding provided by co-occurring motor responses in target-present trials. That is, motor responses may have been essential in initially facilitating participants' learning and application of the task regularities, though they were not required later after attention was already tuned.

Alternatively, other evidence suggests that co-occurring motor-temporal predictions may *not* be essential for using feature-temporal predictions to benefit performance. Some research has shown that temporal attention can affect perceptual systems directly, especially in perceptually demanding tasks (Correa et al., 2005, 2006; Seibold et al., 2023). More specifically, a small number of studies have demonstrated that non-spatial feature-temporal predictions can enhance performance independently of motor-temporal predictions. Firstly, Thomaschke et al. (2016) investigated whether participants formed time-based expectations about both target features and motor responses likely to occur after a short or long interval. In their task, the majority of trials upheld temporal regularities in both features and responses simultaneously (i.e., the regularities were confounded). A minority of trials preserved one regularity while disrupting the other, allowing the performance effects associated with each form of temporal expectation to be tested separately. Their results provided indirect evidence that participants simultaneously formed distinct time-based expectations of comparable strength for both target features and responses.

More direct evidence comes from recent studies by Echeverria-Altuna et al. (2024) and Gao et al. (2025), which found performance benefits for feature-temporally predictable targets under both spatial and motor uncertainty. In these experiments, participants more efficiently detected targets of a particular colour that appeared at a predictable time within a stimulus stream, compared to target colours with no temporal regularity. Regardless of colour, all targets required a left or right response with equal probability, according to their location relative to a fixation cross, making exact

motor responses temporally unpredictable. These findings suggest that performance benefits for feature-temporally predictable targets *can* occur independently of temporally tuned motor preparation. However, effects were observed in tasks performed while maintaining fixation, where targets appeared at only one or two locations with no concurrently visible distractors. For DVS tasks, which simulate busier real-world contexts where concurrent targets and distractors compete for attention across varied times and locations, it is possible that co-occurring temporally predictable motor responses are required to scaffold the learning and use of regularity-based feature-temporal predictions.

The present study addresses this by investigating whether feature-temporal and motor-temporal regularities can be independently learned and used to guide behaviour in an online DVS task. The task was similar to those in Chapter 2 but employed stimuli that decoupled target colour from response, allowing feature- and motor-temporal regularities to be unconfounded. Each target appeared either early or late during a trial, in one of two colours, and required one of two responses. Targets were spatially unpredictable. Participants were assigned to one of four between-subjects conditions: in the 'feature-temporal' (FT) condition, only target colour was temporally predictable, in the 'motor-temporal' (MT) condition, only response was temporally predictable; in the 'feature-motor-temporal' (FMT) condition, both target colour and response were temporally predictable (as in Chapter 2); in the neutral (N) condition, neither was temporally predictable. During an initial learning session, target colours and/or responses always occurred at their predicted time (where relevant). In a subsequent testing session, target colours and/or responses were less temporally predictable.

I tested whether participants in each of the FT, MT, and FMT conditions showed improved performance for temporally likely versus unlikely targets in the testing session. For the FMT condition, I aimed to replicate the performance benefits observed in Chapter 2. For the FT and MT conditions, I

assessed whether similar benefits emerged for feature- or motor-temporal regularities in isolation. Performance differences in the testing session may partly reflect costs for temporally unlikely targets, rather than performance benefits for temporally likely targets. Therefore, I also compared learning session performance in the FT, MT and FMT conditions to that in the N condition to determine whether each temporal regularity produced true performance benefits relative to a neutral baseline.

To foreshadow the results, all three of the temporally contingent regularities (FT, MT, and FMT) led to some performance benefit relative to the N condition. Effects were less robust for the FT condition, suggesting weaker benefits in the absence of motor-temporal predictability. Unlike in Chapter 2, effects of temporally contingent predictions emerged more strongly at late, rather than early, times during trials. Also, in contrast to Chapter 2, no significant testing-session benefits were found for temporally likely versus unlikely targets in any condition. Possible reasons for these unexpected yet informative findings are discussed.

3.3 Methods

3.3.1 Participants

I recruited participants using *Prolific* (www.prolific.co). All participants were aged between 18 and 40 years and reported normal or corrected vision (including colour vision), fluency in English, no ongoing mental health conditions, and not taking any psychoactive medication. Participants were required to have completed at least five previous studies using Prolific and have had at least 90% of their previous submissions approved. All participants gave informed consent and were compensated at a rate of approximately £10 per hour, based on an expected completion time of 55 minutes. All experimental procedures were reviewed and approved by the University of Oxford Medical Sciences Interdivisional Research Ethics Committee.

The final sample consisted of 256 participants (105 female, 151 male; mean age = 29.06 ± 5.83 (*SD*); two participants did not provide their age). Sixty-four of these participants were assigned to each of the four conditions: *Neutral (N)* (25 female, 39 male; mean age = 29.28 ± 5.68), *Feature-Temporal (FT)* (31 female, 33 male; mean age = 28.00 ± 5.57), *Motor-Temporal (MT)* (28 female, 36 male; mean age = 29.06 ± 6.06; one participant did not provide their age), and *Feature-Motor-Temporal (FMT)* (21 female, 43 male; mean age = 29.89 ± 5.99; one participant did not provide their age).

Sample size was determined based on a *G*Power* analysis (G*Power 3.1; Faul et al., 2007), which showed that a sample size of 64 per condition would have 80% power to detect a medium effect of *condition* on performance in a two-tailed *between-subjects t*-test with significance criterion .05. Within a single condition, a G*Power analysis reported that the sample size 64 had over 95% power to detect a medium effect of *target likelihood* on performance, in a two-tailed *repeated-measures t*-test. This latter effect size used for power analysis was based on the medium-sized effect of target predictability on performance found in Chapter 2 Experiment 2 (see Testing Session: Behavioural Performance).

3.3.2 Apparatus

Each participant completed the study using their own personal computer or laptop and was asked to sit 60 cm (approximately an arm's length) from their screen. The only equipment requirement was that the device have a screen measuring at least 12" (standard 16:9 aspect ratio). The experimental script was generated using *PsychoJS* (PsychoPy v2023.2.3; Peirce et al., 2019) and hosted online using *Pavlovia* (www.pavlovia.org). The experimental code, for use with *PsychoPy*, can be found on OSF (https://osf.io/jbd86/files). The digital consent form participants completed was created and hosted using *Qualtrics* (www.qualtrics.com).

3.3.3 Dynamic Visual Search Task

Stimuli. The search display contained a selection of the target and distractor stimuli (coloured discs) shown in Figure 3.1A. Stimuli appeared at various times and locations on a static 1/F greyscale noise background (Figure 3.1B). A video demonstration of a trial can be found here: https://osf.io/jbd86/files. The background was presented at an approximate size of 26.60 cm x 15.00 cm for all participants, based on estimates of their screen's pixel scale (see Procedure). Background images were generated in advance using *MATLAB* (MATLAB v2020a; The MathWorks Inc, 2020). A different background image was shown on each trial, in a randomized order. The stimulus set consisted of all combinations of three colours ('pink' (RGB(197, 119, 152); 'blue' (RGB(70, 155, 191)); and 'green' (RGB(129, 155, 70))) and three types of black markings (triangular notches on both sides, a triangular notch on the right and a rectangular notch on the left, or a triangular notch on the left and a rectangular notch on the right). Each stimulus was presented with a diameter of 1.05 cm, approximately one degree of visual angle (DVA).

Targets were defined as specific colour-marking combinations, the same for all participants. Targets were pink or blue, *not* green, and had a rectangular notch on one side, *not* two triangular notches (Figure 3.1A). Targets with a rectangular notch on the left required a left response, and targets with a rectangular notch on the right required a right response. The rectangular and triangular markings were intentionally difficult to discriminate. This was done to encourage participants to use target colour as the primary basis for their attentional guidance, as in the experiments in Chapter 2, such that they would first need to fixate discs of target colour before they could discriminate their markings. Non-target stimuli appeared as distractors. Distractors could share either their colour or their markings with a target, but not both (Figure 3.1A).

Exactly nine stimuli appeared during each trial, at least one of which was a target. On a given trial, either one or two targets appeared. The remaining eight or seven stimuli, respectively, were

distractors. No target stimulus appeared twice in a single trial. Each of the three green distractor stimuli appeared exactly once per trial. On trials where zero, one, or two pink targets appeared, the sole pink distractor stimulus appeared three times, twice, or once, respectively. On trials with zero, one, or two blue targets, the sole blue distractor stimulus appeared three times, twice, or once, respectively. Exactly three stimuli of each colour, whether targets or distractors, appeared per trial.

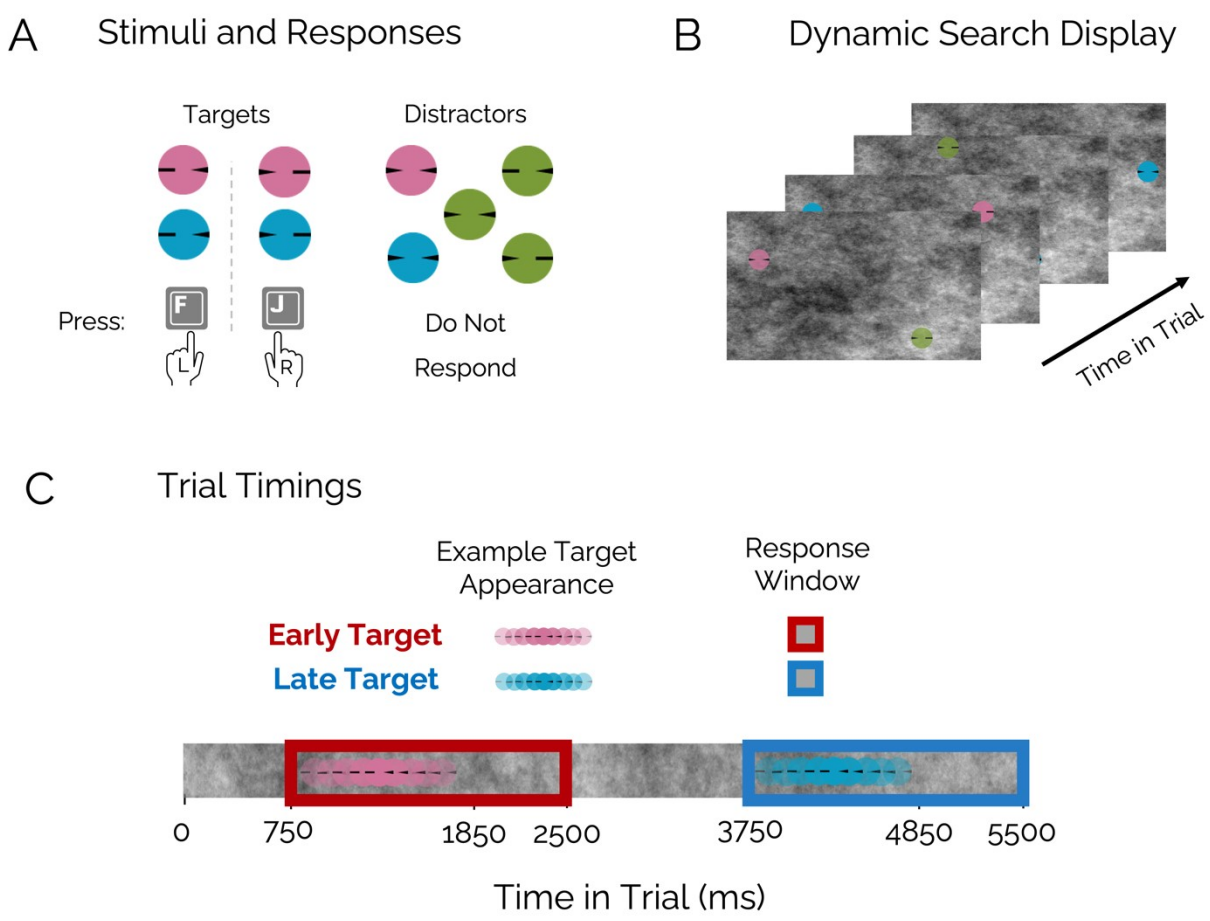


Figure 3.1. DVS schematic. **(A)** Target and distractor stimuli that appeared during trials. Targets were pink or blue *and* had a rectangular notch. A rectangular notch on the left or right of a target required an 'F' or 'J' response, respectively. Distractors were green and/or had two triangular notches. **(B)** Illustration of a DVS trial where stimuli faded in and out transiently at different times and locations. A video demonstration of a trial can be found here https://osf.io/jbd86/files. **(C)** Schematic of trial timings. All targets onset early at 750 ms or late at 3750 ms. Note that in the majority of trials only one target appeared, at only one of the onset times, while in a minority of trials two targets appeared, one at each onset time. After onset, targets were visible for 1100 ms and participants had 1750 ms to respond correctly. The target stimuli that could appear at each onset time depended on the condition (N, FT, MT, or FMT) and the experimental session (Learning or Testing).

General Timings. All trials lasted 5500 ms. Stimuli faded in from zero to maximum opacity of 1 over 250 ms, remained at maximum opacity for 600 ms, then faded back out to zero opacity over 250 ms. The total duration during which stimulus opacity was above zero was 1100 ms. As for Chapter

2, the '*onset time*' of a stimulus was the time it began fading in during a trial, i.e., the time when the stimulus's opacity first crossed zero.

Target Timings (Predictable). A trial contained either one or two target appearances. Each target appeared either early, at 750 ms, or late, at 3750 ms (Figure 3.1C). Across the experiment, a target was equally likely to appear at either onset time (early or late), to be either colour (pink or blue), and to require either response (left or right). However, the probability of a target appearing in a particular colour and/or requiring a particular response could be temporally locked to the early and late onset times.

The nature of this temporal predictability varied between the conditions assigned to participants (see Regularity Conditions below). As well as depending on the participant's condition, the exact probability of each target colour and/or response appearing at a given onset time depended on the experimental session (see Learning and Testing Sessions). I did not inform participants of any temporal regularities in the task until after the experiment.

Regularity Conditions. Within each condition, the assignment of each target colour and/or response as likely-early or likely-late was counterbalanced between participants. Below I explain each potential regularity condition:

Neutral (N): In the baseline condition, *N*, neither target colour nor response varied predictably with onset time. Each possible combination of target colour and response was equally likely to appear early or late (Figure 3.2A). The only constraint was that, in a trial where two targets appeared, they could not share both colour *and* response i.e., the same exact target stimulus could not appear twice.

Feature-Temporal (FT): In the *FT* condition, target colour varied predictably with onset time e.g., pink targets were likely early and blue targets were likely late (Figure 3.2B). Note that, in this context, *feature* refers specifically to the (assumed) attention-guiding stimulus feature of colour, and

not to the stimulus markings. Each motor response was equally likely at each onset time. In a trial where two targets appeared, only one target in each colour could appear, but they could both require the same response.

Motor-Temporal (MT): In the *MT* condition, target response varied predictably with onset time e.g., left responses were likely early and right responses were likely late (Figure 3.2C). Each target colour was equally likely at each onset time. In a trial where two targets appeared, only one target requiring each response could appear, but targets could share the same colour.

Feature-Motor-Temporal (FMT): In the *FMT* condition, both target colour *and* response varied predictably with onset time e.g., blue targets that required a right response were likely early, and pink targets that required a left response were likely late (Figure 3.2D). In a trial where two targets appeared, only one target in each colour, and only one target requiring each response, could appear. These regularities are analogous to those in Chapter 2, where both target features and responses varied predictably with onset time, and where each target stimulus appeared no more than once per trial.

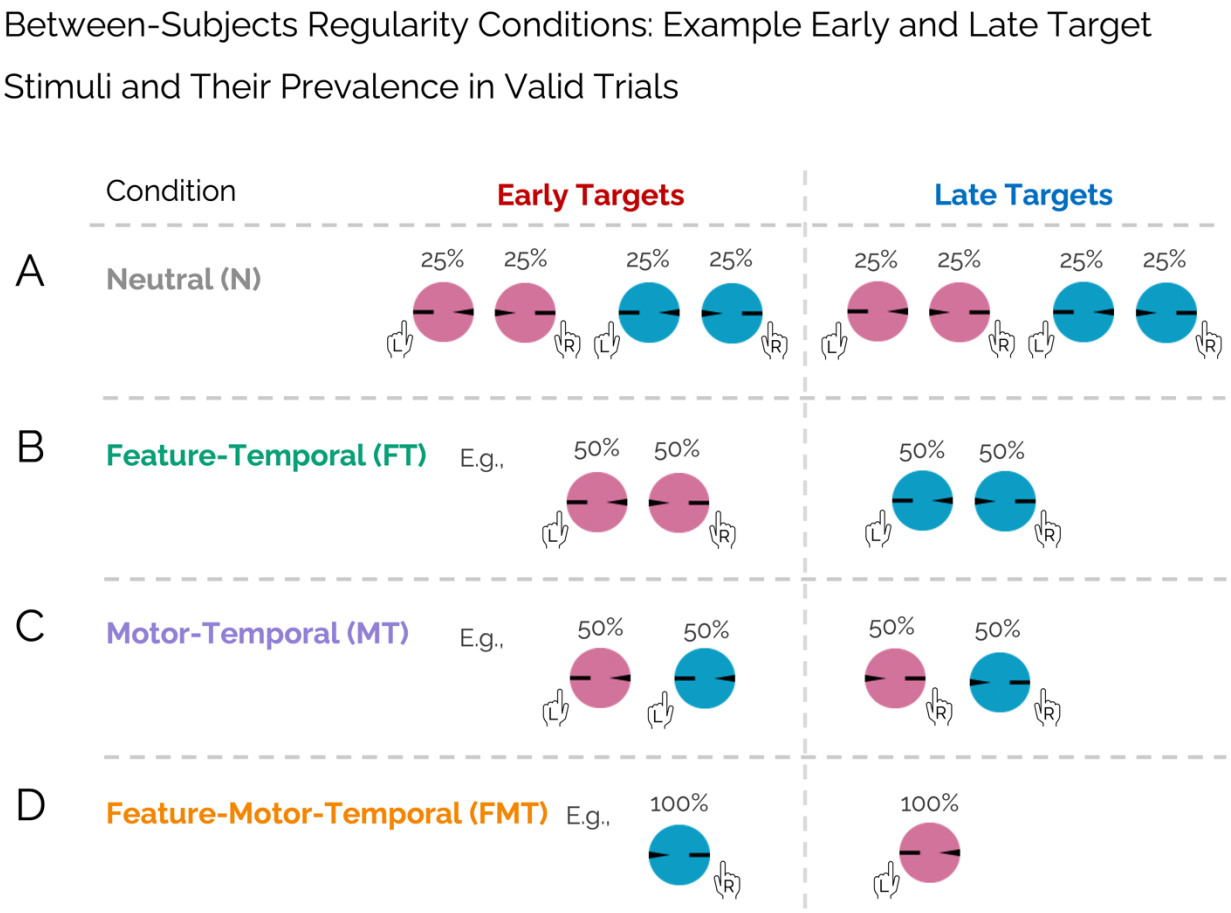


Figure 3.2. Example target stimuli and responses at each onset time, along with their relative prevalence across trials for each regularity condition. For *valid* trials only. **(A)** In the **N** condition, whether a target appeared early or late, each target (combination of colour and response) was equally likely without replacement (i.e., the same target could not appear twice in a trial). **(B)** In the **FT** condition, if a target appeared early, it was always one colour, and if a target appeared late, it was always the other colour. Both responses were equally likely to occur early or late. **(C)** In the **MT** condition, early targets always required one response, and late targets always required the other response. Both early and late targets were equally likely to be pink or blue. **(D)** In the **FMT** condition, early targets were always one specific colour *and* required one specific response, while late targets were always the other colour *and* required the other response.

Distractor Timings. Distractors were temporally unpredictable. For every trial, each distractor was assigned an onset time between -850 ms and 5250 ms. The negative onset times served as dummy values to allow distractors to be part-way through their appearance at the start of a trial, effectively equating the amount of distraction throughout the trial. This assignment was

random except for requiring that no stimulus onset within 100 ms of another stimulus. As stimuli were visible for up to 1100 ms, multiple stimuli could be visible at the same time.

Stimulus Locations. All targets and distractors were spatially unpredictable across trials. Nine locations were pseudo-randomly generated on every trial, and each location assigned to one stimulus. To generate the locations, I first divided the search display into a grid of nine equally-sized cells separated by borders. I then randomly selected one set of (x, y) pixel coordinates from each cell. These coordinates corresponded to the location of a stimulus centre. The borders between cells prevented stimuli from overlapping with one another or with the edge of the background. Specifically, the borders were such that the centre of each stimulus was at least 2.5 DVA from the centre of another stimulus and/or at least 1 DVA from all edges of the background image. The location of each stimulus remained constant as it faded in and out.

Identifying Targets. Participants were tasked with finding and identifying all targets that appeared in a trial. They were instructed to report targets with a key press, as quickly as possible. Left responses, for targets with a left-sided rectangular notch, were made with the 'F' key. Right responses, for targets with a right-sided rectangular notch, were made with the 'J' key (Figure 3.1A). Following target onset, participants had 1750 ms to provide a correct response (Figure 3.1C). This response window lasted 650 ms after the target disappeared, to allow for post-stimulus processing and delayed responses. Any response made outside of this window was classed as a false alarm. Participants were told that either one or two targets could appear in a single trial but were not told how many targets to expect on a specific trial.

Feedback. Feedback was given at the end of each trial. "Correct" was shown whenever correct responses were made to all targets within the response window, and no false alarms occurred. "Incorrect" was displayed whenever participants missed a target, responded with the incorrect key, or made a false alarm.

Learning and Testing Sessions. Participants completed a learning session followed by a testing session, though they were not made aware of this. The learning session consisted of the first five experimental blocks, and the testing session consisted of the final, sixth block. Each block contained 60 DVS trials randomly intermixed: 12 trials with two targets, one early and one late (20%), 24 trials with one target that appeared early (40%), and 24 trials with one target that appeared late (40%).

All learning trials were '*valid*', meaning targets always upheld the regularities associated with the participant's condition, if any. In other words, for participants assigned to the FT, MT, and FMT conditions, a target's colour and/or response was entirely predictable based on its onset time. Figure 3.2 illustrates example target stimuli that could appear at each onset time in valid trials, for each regularity condition. For the example FT regularities, every target that onset early during the learning session was pink, and every target that onset late was blue (Figure 3.2B).

During the testing session, target colours and/or responses were less predictable. Regularities from the preceding learning session were preserved in two thirds of trials ('valid' trials) but were reversed in one third of trials ('*invalid*' trials). During an invalid trial, whenever a target with a particular colour and/or response appeared, it appeared at the onset time previously predictably associated with the other colour and/or response. For the example FT regularities (Figure 3.2B), targets that onset early in an invalid trial were blue, and targets that onset late were pink. Note that invalid targets in the FMT condition violated temporal regularities regarding both colour *and* response simultaneously.

For the N condition, learning and testing blocks did not differ. This condition contained no valid or invalid trials because both target colours and responses were always equally likely at each onset time (Figure 3.2A).

3.3.4 Procedure

Participants first provided informed consent and demographic information via *Qualtrics* (www.qualtrics.com). They were then redirected to *Pavlovia* (www.pavlovia.com) to complete the DVS task. I asked participants to complete the task in a quiet place and not to listen to music. So that stimuli could be scaled to approximately the same size for all participants, I first measured the pixel scale of each participant's screen. To measure this, I asked participants to rescale a digital rectangular image to match the size of a standard bank or ID card in reality, employing the *ScreenScale* routine for PsychoPy (Morys-Carter, 2023). Despite this calibration, some variation in stimulus size between participants likely remained due to inaccurate scaling.

Following screen scaling, participants read the DVS instructions and were shown a video demonstration of a trial. They then completed a short training session to ensure they had learnt which stimuli were targets and the required responses. During each of 30 training trials, participants were shown one target or distractor stimulus and instructed to respond with the appropriate 'F' or 'J' key only if that stimulus was a target. Each of the four target stimuli were shown five times, and each distractor stimulus was shown twice. Participants were required to get 80% of training trials correct to continue, else training repeated. On average, participants completed the training 1.05 times before moving on.

Following training, participants completed 15 practice DVS trials with condition-specific regularities i.e., valid trials. These included three two-target trials, six early-target-only trials, and six late-target-only trials, randomly intermixed. Participants progressed if they received 'correct' feedback on at least 50% of practice trials, otherwise practice repeated. On average, participants completed the practice session 1.35 times before progressing.

After practice, participants completed the six blocks of the DVS task, lasting approximately 55 minutes. Participants could take breaks lasting up to one minute between blocks. After each block, participants were told their percentage of 'correct' trials in that block, and their average RT.

3.3.5 Variables of Interest

The experimental design served two main questions. The first asked whether each temporally contingent regularity (FT, MT, and FMT) benefitted performance compared to baseline (N) during the learning session. Complementary to this, the second question asked whether participants in each of the FT, MT, and FMT conditions used the relevant temporally contingent regularity to guide their behaviour over time during trials. Data from the testing sessions addressed this second question: I assessed for performance benefits for temporally valid compared to invalid targets, for each of the FT, MT, and FMT conditions separately. The FMT comparisons aimed to replicate findings from Chapter 2, while the FT and MT comparisons aimed to extend these findings by testing for benefits of feature- and motor-temporal regularities individually.

Across these analyses, the IES metric (Townsend & Ashby, 1983) served as the dependent measure of performance. As in Chapter 2, IES was calculated by dividing mean RT by the proportion of target hits, with lower IES indicating more efficient performance. Hits were a binary measure indicating whether a target had been correctly identified within the time limit (hit; 1), or not (0). RTs were calculated as the time, in ms, between the onset of a target and the first correct key press within the response window.

Both analyses omitted targets that had appeared second during two-target trials. As no target stimulus appeared twice in any two-target trial, the second target stimulus could be considered partially cued by the first. Omitting these targets, therefore, avoided conflating the effects of temporally contingent regularities with these potential cueing effects.

Learning Session: Performance Benefits for Regularities Between Conditions. The analysis of performance between conditions employed a mixed-subjects design. I compared performance identifying targets between *conditions* between subjects (N, FT, MT, or FMT), and between *target onset time* (early or late) and *learning block number* (1, 2, 3, 4, or 5) within subjects. For each participant, I calculated an IES value for targets falling into each combination of onset time and block number. Ten IES values were therefore calculated per participant, corresponding to each point in Figure 3.3C for a single condition. Learning trials were analysed to avoid effects related to behavioural changes following invalid trials.

I hypothesised that, if participants had used the feature-temporal, motor-temporal, or feature-motor-temporal regularities to improve at identifying targets, then I would find significantly better performance in the FT, MT, or FMT condition, respectively, compared to the N condition. I also hypothesised that, based on results from Chapter 2, these condition-wise benefits may be more pronounced for targets that appeared early during trials, and for targets in later blocks.

Testing Session: Investigating Performance Benefits for Temporally Predicted Targets Within Conditions. The analysis of performance between temporally valid and invalid targets in the testing session employed a within-subjects design. This analysis was performed separately for each of the FT, MT, and FMT conditions, using an identical procedure. Data from the N condition was not analysed here.

For this analysis, I compared performance identifying targets between *onset time* (early or late) and *target likelihood* (likely-early or likely-late). What constituted a likely-early or likely-late target varied with condition (see Regularity Conditions). For each participant, I calculated their IES for targets at each combination of levels of onset time and likelihood (corresponding to each bar in Figure 3.4A, B, & C).

For participants in a given condition, I hypothesised that, if they had used the regularities from the learning session to adaptively guide their behaviour over time during trials, then temporally valid targets would be identified significantly more efficiently than temporally invalid targets. In other words, that likely-early targets would be identified more efficiently than likely-late targets when targets onset early, and likely-late targets would be identified most efficiently when targets onset late. Further, as was found in Chapter 2, I anticipated that these performance benefits may be most pronounced for early targets.

3.3.6 Statistical Analysis

All analyses used R (R Core Team, 2024) and plots were created using the *ggplot2* package (Wickham, 2016). In all cases, I used a two-tailed 5% error criterion to test for significance. Full datasets, and data cleaning and analysis scripts, are available on OSF https://osf.io/jbd86/files.

Data Cleaning. Data cleaning methods were based on those in Chapter 2. Data from each regularity condition, and from each of the learning and testing sessions, were cleaned separately using the same procedure. If the procedure excluded either a participant's learning or testing session data, then all of their data were excluded. I tested additional participants to replace any excluded participants and repeated data cleaning until my pre-determined sample size of 64 per condition was reached. As such, I replaced 8, 14, 10, and 11 participants from the N, FT, MT, and FMT conditions, respectively.

Firstly, all data were excluded from any participant who did not finish the experiment, or who reported in a debrief that I should not analyse their data. Data were then excluded from participants with low accuracy. The threshold for accuracy required participants to have correctly identified (hit) at least 50% of targets in both sessions. Participants' mean hits for each session was also required to be within 3 *SD*s of the mean hits across *all* participants from the same condition within that session.

On the target level, I used RTs to remove premature or outlier responses. Firstly, data associated with an RT < 200 ms were removed. Then, within participant and within session, responses were removed if their RT was more than 3 *SD*s slower than the participant's median RT. I planned to exclude all data from any participant for whom these two steps removed more than one third of their trials. However, this was not the case for any participant. For the learning session in each condition, these steps removed 1.64% (N), 1.66% (FT), 1.81% (MT), and 1.56% (FMT) of RT data from the final sample. For the testing sessions, these steps removed 1.45% (N), 1.91% (FT), 1.77% (MT), and 1.60% (FMT) of RT data from the final sample. Lastly, all data were excluded from participants whose median RT was more than 3 SDs away from the median RT across *all* participants for the relevant session and condition.

Learning Session: Performance Between Conditions. For the learning session data, I analysed the effects of *condition* (N, FT, MT, FMT), *onset time* (early or late), *block number* (1-5), and their interactions on IES with a 4 x 2 x 5 mixed ANOVA. Here, and for all subsequent ANOVAs, I used the *ezANOVA* function from the *ez* package (M. A. Lawrence, 2016). If required, IES values were transformed prior to analysis to meet the assumption of normality. Here, and in subsequent analyses, transformations followed recommendations of the *boxcox* function of the *MASS* package (Venables & Ripley, 2002). A significant main effect of block number was followed up with a repeated-measures *t*-test comparing IES scores in the first and final blocks only. I had hypothesised, based on the results of Chapter 2, that the effect of condition would depend significantly on onset time and block number. As such, significant interactions between condition and onset time or block number were followed up with pre-planned two-sample *t*-tests. Follow-up analyses for interactions with onset time investigated whether performance in each of the FT, MT, and FMT conditions differed significantly from the N condition for each onset time individually. Follow-up analyses for interactions with block number investigated whether performance in each of the FT, MT, and FMT conditions differed

significantly from the N condition for the first and last learning block individually. Additional *t*-tests were supplemented by Cohen's *d* values, calculated using untransformed data, and Bayesian *t*-tests performed on transformed data using the *BayesFactor* package (Morey & Rouder, 2022). Interpretations for different values of the Bayes factor are given in Table 2.2.

Supplementary analyses investigated the effects of condition, onset time, and block number on hits and RT individually. Results of these analyses are visualised in Supplementary Figure 7.10 and Supplementary Figure 7.11, and provided in full in Supplementary Table 7.10 and Supplementary Table 7.11, respectively.

Testing Session: Performance for Temporally Valid and Invalid Targets Within Conditions. I ran separate 2 x 2 repeated-measures ANOVAs to analyse the effects of onset time, target likelihood, and their interaction, on IES for each of the FT, MT, and FMT conditions. As I had hypothesised that the effect of target likelihood would depend on onset time, I planned to follow up any significant interactions with repeated-measures *t*-tests separately analysing the effect of target likelihood at each onset time.

Supplementary analyses investigated these effects of onset time and target likelihood on hits and RT individually, for each of the three conditions. These supplementary results are visualised in Supplementary Figure 7.12 and are provided in Supplementary Table 7.12 to Supplementary Table 7.17.

3.4 Results

3.4.1 Learning Session: Performance Benefits Between Regularity Conditions

The analysis provided some evidence of performance benefits for conditions with feature- and/or motor-temporal regularities compared to without these regularities. Benefits varied with onset time and block number (Figure 3.3). In line with *boxcox* recommendations, IES values

underwent a reciprocal squared transformation prior to analysis. The full ANOVA output is provided in Table 3.1. The ANOVA revealed a significant main effect of onset time on IES ($p < .001$). Overall, targets were identified more efficiently when they onset late during trials (M_{IES} = 1051 ms, SD_{IES} = 98 ms) compared to early (M_{IES} = 1128 ms, SD_{IES} = 98 ms). The main effect of block number was also significant ($p < .001$, Greenhouse-Geisser correction). Targets were identified significantly more efficiently during the final learning block (M_{IES} = 1025 ms, SD_{IES} = 95ms) than during the first (M_{IES} = 1179 ms, SD_{IES} = 95ms; $t(255) = -17.20$, $p < .001$, $d = 0.91$, $BF_{10} > 1000$). The main effect of condition was not significant ($p = .059$). Overall, IES did not differ significantly between the regularity conditions. However, the ANOVA did reveal significant interactions between condition and onset ($p = .001$; Figure 3.3A), and between condition and block number ($p = .039$, Greenhouse-Geisser correction; Figure 3.3B). No further interactions were significant.

Table 3.1

Learning Session IES Full mixed ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Condition	2.52	3	252	.059	.019	NA
Onset	**111.07**	**1**	**252**	**< .001**	**.045**	**NA**
Block Number	**132.64**	**3.47[1]**	**874.44[1]**	**< .001[1]**	**.077**	**0.87**
Condition : Onset	**5.40**	**3**	**252**	**.001**	**.007**	**NA**
Condition : Block Number	**1.90**	**10.41[1]**	**874.44[1]**	**.039[1]**	**.004**	**0.87**
Onset : Block Number	0.53	3.77[1]	949.52[1]	.702[1]	< .001	0.94
Condition : Onset : Block Number	1.24	11.30[1]	949.52[1]	.255[1]	.001	0.94

Note. Significant predictors are shown in bold. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

Condition x Onset Time. I followed up the significant interaction between condition and onset time with Welch's *t*-tests. Separately for each onset time, IES scores from each of the FT, MT, and FMT conditions individually were compared to the N condition. When targets onset early, performance did not differ significantly between the N and FT conditions ($t(120.39) = -1.00$, $p = .321$, $d = 0.01$, $BF_{10} = 0.30$), or between the N and FMT conditions ($t(122.55) = -0.76$, $p = .452$, $d = 0.07$, $BF_{10} = 0.24$). In contrast, participants in the MT condition (M_{IES} = 1089 ms, SD_{IES} = 145 ms) identified early targets significantly more efficiently than participants in the N condition (M_{IES} = 1145 ms, SD_{IES} = 177

ms; $t(125.77) = -2.00$, $p = .048$, $d = 0.35$), though the Bayes' factor indicated only anecdotal evidence for this difference ($BF_{10} = 1.14$; see Table 2.2 for interpretation of BF_{10}).

When targets onset late, greater differences between conditions were found. Participants in the FT condition (M_{IES} = 1056 ms, SD_{IES} = 171 ms) identified late targets significantly more efficiently than participants in the N condition (M_{IES} = 1099 ms, SD_{IES} = 152 ms; $t(116.08) = -2.07$, $p = .041$, $d = 0.27$), though the Bayes' factor classed evidence for this difference as only anecdotal ($BF_{10} = 1.29$). Participants in the MT condition (M_{IES} = 1032 ms, SD_{IES} = 130 ms) also identified late targets significantly more efficiently than N participants ($t(125.76) = -2.98$, $p = .003$, $d = 0.48$), with this difference supported by more moderate evidence ($BF_{10} = 9.71$). Lastly, there was strong evidence for a difference between the FMT and N conditions ($t(120.65) = -3.79$, $p < .001$, $d = 0.59$, $BF_{10} = 102.98$), with FMT participants (M_{IES} = 1016 ms, SD_{IES} = 125 ms) identifying late targets significantly more efficiently than N participants. Though these differences between conditions for late targets appear more pronounced during later blocks (Figure 3.3C), the three-way interaction between condition, onset, and block number was not statistically significant ($p = .255$, Greenhouse-Geisser correction).

These findings of performance benefits for late targets for each of the FT, MT, and FMT conditions, relative to the N condition, called to question whether there were also significant differences among the various predictive conditions. Such effects would indicate potential differences in the strength of each form of temporal prediction. Two additional, exploratory *t*-tests compared IES values for late targets between FT and FMT participants, and between MT and FMT participants. As these comparisons were not planned, I used a Bonferroni-corrected significance level .017 (for three unplanned follow-up comparisons, including that below in Condition x Block Number). No significant difference in performance for late targets was found between the MT and FMT conditions ($t(122.52) = -1.07$, $p = .287$, $d = 0.12$, $BF_{10} = 0.32$). Late target performance also did not

differ significantly between the FT and FMT conditions (t(125.05) = -1.40, p = .165, d = 0.26), though evidence for this null effect was only anecdotal (BF_{10} = 0.46).

Condition x Block Number. The significant two-way interaction between condition and block number also required further investigation. For the first and final learning block separately, I ran three Welch's t-tests which each compared performance between the N condition and one of the FT, MT, or FMT conditions.

For the first learning block, there were no significant differences between IES values in the N condition and in the FT (t(124.38) = -0.79, p = .432, d < 0.01, BF_{10} = 0.25), MT (t(125.03) = -1.87, p = .064, d = 0.33), or FMT (t(125.18) = -0.73, p = .465, d = 0.02, BF_{10} = 0.24) conditions (Figure 3.3B). Though, evidence for this null effect was only anecdotal for the MT condition (BF_{10} = 0.91).

Some differences between conditions were more pronounced at the end of the learning session, as hypothesised (Figure 3.3B). Overall, IES values did not differ significantly between the FT and N conditions in the final learning block (t(124.03) = -1.77, p = .079, d = 0.24), though evidence for this null effect was only anecdotal (BF_{10} = 0.78). Final-block IES values in the MT condition (M_{IES} = 1006 ms, SD_{IES} = 104 ms) were significantly lower than in the N condition (M_{IES} = 1061 ms, SD_{IES} = 155 ms; t(125.18) = -2.46, p = .015, d = 0.42), though evidence for this was only anecdotal (BF_{10} = 2.85). Final-block IES values were also significantly lower in the FMT condition (M_{IES} = 1007 ms, SD_{IES} = 135 ms) than the N condition (t(120.54) = -2.70, p = .008, d = 0.37, BF_{10} = 4.89). An additional exploratory t-test compared final-block performance between the MT and FMT conditions, as both showed benefits compared to N, though no significant difference was found (t(116.28) = -0.62, p = .538, d = -0.01, BF_{10} = 0.22).

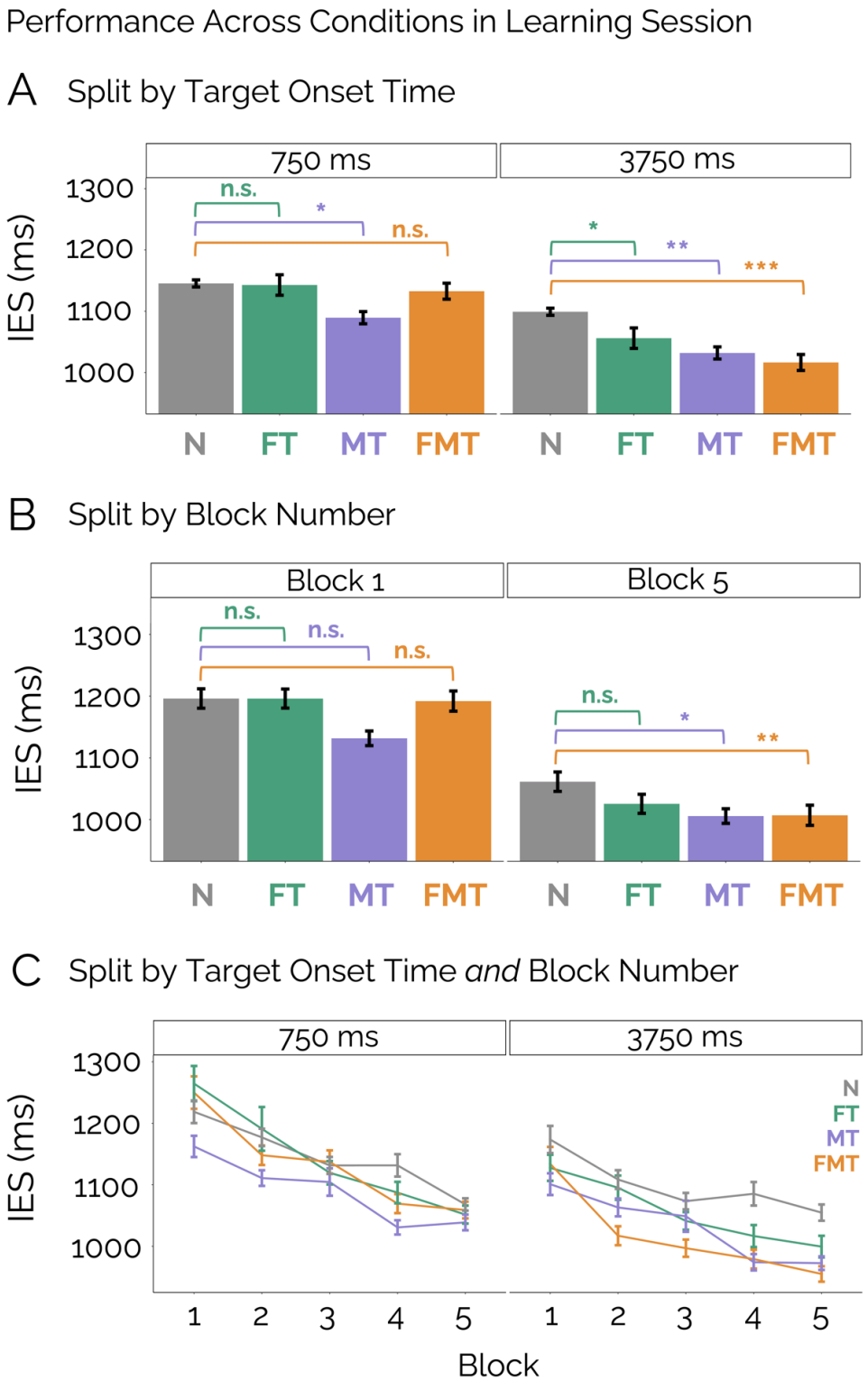


Figure 3.3. Mean (untransformed) IES for identifying targets during the learning session, for participants in each of the N, FT, MT, and FMT regularity conditions. Here, and in Figure 3.4, error bars represent ±1 standard error (*SE*) around the mean. The statistical significance of follow-up

analyses comparing performance in each of the FT, MT, and FMT conditions to the N condition is indicated with asterisks: *** = $p < .001$, ** = $p < .01$, * = $p < .05$, n.s. = not significant. **(A)** IES in each condition split by whether targets appeared early (750 ms onset) or late (3750 ms onset) during trials. **(B)** IES in each condition split by whether targets appeared in the first (Block 1) or last (Block 5) block of the learning session. **(C)** IES in each condition split by both target onset times and all learning session blocks.

3.4.2 Interim Discussion

Independent of condition, identification efficiency during the learning session depended significantly on onset time and block number. Participants identified targets more efficiently when they appeared late during trials, rather than early. This is consistent with previous findings that longer foreperiods can lead to faster responses to targets (Niemi & Näätänen, 1981). Given that at least one target appeared during every trial, this finding may also reflect participants' certainty that a target would appear late, if one had not appeared early. This is in contrast to the tasks in Chapter 2, where some trials contained zero targets. Participants also identified targets more efficiently when they appeared during the final learning block compared to the first, consistent with overall performance having improved during learning.

The effects of condition on performance varied significantly with target onset time. While this was hypothesised, I had anticipated that the performance benefits for the FT, MT or FMT conditions, relative to N, would be most pronounced for early-onset targets. This was due to multiple analyses in Chapter 2 finding greater evidence of temporal predictions shaping behaviour at early, rather than late, times during trials. In contrast to this, performance differences between conditions were more pronounced when targets onset *late*. When targets onset early, only performance in the MT condition was significantly more efficient than in the N condition. Further, the evidence for this difference was only classed as anecdotal, meaning it should be interpreted with caution. When targets onset late, performance in each of the FT, MT, and FMT conditions benefitted significantly compared to the N condition. This suggests participants were better at using the temporally

contingent regularities, particularly the FT and FMT regularities, to benefit performance at later times during trials. The unexpected selectivity of these effects for late, rather than early, targets is noteworthy. Several factors may account for the differences in temporal-specificity between the present findings and those in Chapter 2 (see General Discussion).

For late-onset targets, performance benefits relative to N were least pronounced for the FT condition (Figure 3.3A), and the evidence for this difference was only anecdotal. The performance benefit relative to N was numerically largest for the FMT condition, suggesting feature- and motor-temporal regularities may benefit performance to the greatest extent when combined. Ultimately, however, FMT performance for late targets did not differ significantly to the FT or MT conditions, though the evidence for no difference between the FT and FMT conditions was anecdotal.

Regardless of target onset time, the effects of condition varied significantly with block number. As hypothesised, greater differences between conditions were found at the end of the learning session than at the beginning. This pattern is consistent with performance benefits arising after participants had sufficient opportunity to learn the condition-specific regularities. For the first learning block, performance did not differ significantly from the N condition for any of the FT, MT, or FMT conditions. In the final learning block, performances in the MT and FMT conditions were significantly more efficient than in the N condition, though evidence for the MT benefit was only anecdotal. Numerically, performance in the FT condition was also more efficient than in the N condition (Figure 3.3B), though anecdotal evidence found this difference was not significant. This apparent lack of an effect may be due to the pooling of performance across onset times masking benefits specific to late-onset FT targets (Figure 3.3C).

Overall, the learning session results are consistent with participants having learnt and used the FT, MT, and FMT regularities to benefit performance in some way. If these benefits are, as expected, due to participants in the FT, MT and FMT conditions modulating their search behaviour

during trials based on the temporally expected target colour and/or response, then I would expect performance to have declined when these regularities were violated. The following analysis investigated this by comparing performance for temporally likely and unlikely targets in the testing session.

3.4.3 Testing Session: Performance Benefits for Temporally Likely vs. Unlikely Targets

Unexpectedly, none of the ANOVA analyses (Table 3.2, Table 3.3, and Table 3.4) revealed significant evidence that performance declined when FT, MT, or FMT regularities were violated, compared to upheld.

Feature-Temporal (FT) Condition. In line with *boxcox* recommendations, IES values underwent a reciprocal squared transformation prior to analysis. The ANOVA (see Table 3.2) revealed a significant main effect of onset time ($p < .001$), with participants having identified targets that onset late at 3750 ms (M_{IES} = 1016 ms, SD_{IES} = 82 ms) significantly more efficiently than targets that onset early at 750 ms (M_{IES} = 1053 ms, SD_{IES} = 82 ms). The main effect of target likelihood was not significant ($p = .297$), suggesting no overall difference in efficiency when identifying targets in the likely-early and likely-late colours. The interaction between target likelihood and onset time was also not significant ($p = .674$). Contrary to my hypothesis, participants' efficiency identifying likely-early versus likely-late colour targets did not depend significantly on when targets appeared during trials (Figure 3.4A).

Table 3.2

FT Testing Session IES Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	**23.76**	**1**	**63**	**< .001**	**.027**
Target Likelihood	1.10	1	63	.297	.003
Onset Time : Target Likelihood	0.18	1	63	.674	< .001

Motor-Temporal (MT) Condition. IES values underwent a reciprocal squared transformation prior to analysis. The ANOVA (see Table 3.3) revealed a significant main effect of onset time (p = .015). Participants identified late targets (M_{IES} = 1011 ms, SD_{IES} = 65 ms) significantly more efficiently than early targets (M_{IES} = 1028 ms, SD_{IES} = 65 ms). Interestingly, when targets onset early, performance for the likely-early response was numerically more efficient than for the likely-late target response, while the opposite was true when targets onset late (Figure 3.4B). These trends are consistent with my hypothesis that identifications would be more efficient for targets that upheld, rather than violated the task regularities. Ultimately, however, neither target likelihood (p = .879) nor the interaction between target likelihood and onset time (p = .148) significantly affected IES.

Table 3.3

MT Testing Session IES Full ANOVA Output

Predictor	F	df_1	df_2	p	η^2_G
Onset Time	**6.29**	**1**	**63**	**.015**	**.010**
Target Likelihood	0.02	1	63	.879	< .001
Onset Time : Target Likelihood	2.14	1	63	.148	.005

Feature-Motor-Temporal (FMT) Condition. IES values underwent a reciprocal transformation prior to analysis. The ANOVA (see Table 3.4) revealed a significant main effect of onset time (p < .001), with participants identifying late-onset targets (M_{IES} = 1009 ms, SD_{IES} = 72 ms) significantly more efficiently than early-onset targets (M_{IES} = 1041 ms, SD_{IES} = 72 ms). In contrast to the FT and MT conditions, the main effect of target likelihood was significant (p = .015), with participants responding more efficiently to targets with a likely-late colour and response (M_{IES} = 998 ms, SD_{IES} = 100 ms) than a likely-early colour and response (M_{IES} = 1052 ms, SD_{IES} = 100 ms). This advantage for likely-late targets was numerically greatest when targets appeared late, aligning with my hypothesis (Figure 3.4C). However, the interaction between target likelihood and onset time was ultimately not significant (p = .148).

Table 3.4

FMT Testing Session IES Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	**17.09**	**1**	**63**	**< .001**	**.021**
Target Likelihood	**6.32**	**1**	**63**	**.015**	**.018**
Onset Time : Target Likelihood	1.70	1	63	.197	.004

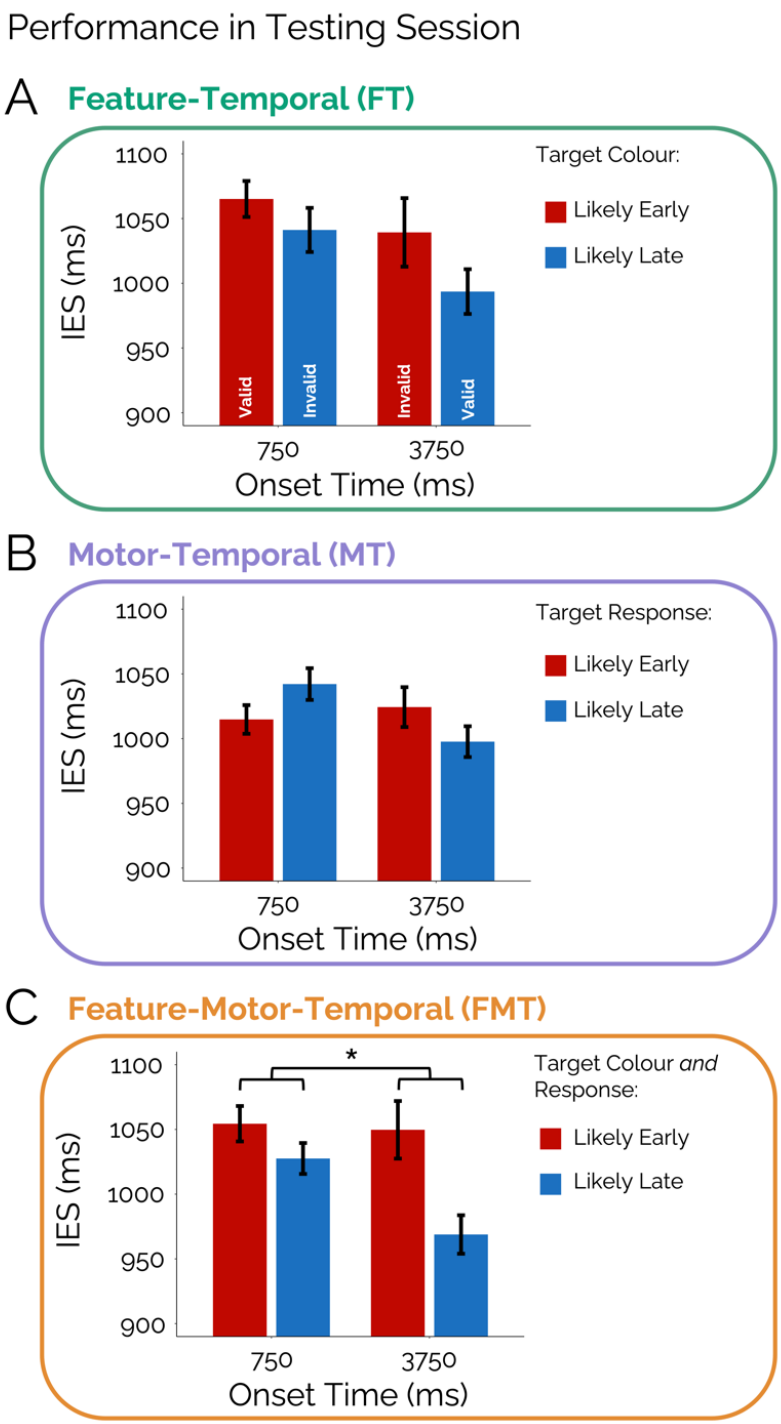


Figure 3.4. Mean (untransformed) IES values for identifying targets in the testing block for likely-early and likely-late targets appearing at each onset time, for participants in each of the FT **(A)**, MT **(B)**, and FMT **(C)** conditions. The statistically significant main effect of target likelihood in the FMT condition is indicated with * = $p < .05$.

3.4.4 Interim Discussion

During the testing session, target identification efficiency in the FT, MT, and FMT conditions depended significantly on onset time. As for the learning session, participants consistently identified late-onset targets more efficiently than early-onset targets.

The main effect of target likelihood did not significantly affect performance in either the FT or MT conditions. That is, participants' efficiency in identifying targets was not significantly affected by whether the target colour (FT) or response (MT) had been predictably associated with the early or late onset time. In contrast, target likelihood had a significant effect on performance in the FMT condition. Specifically, targets were identified significantly more efficiently when their colour and response were predictably associated with the late onset time (likely-late) compared to the early onset time (likely-early), regardless of when targets actually appeared.

Contrary to my hypothesis, and to findings in Chapter 2, the effect of target likelihood did *not* interact significantly with onset time for any condition, including FMT. This suggests that FMT participants consistently biased their attention more toward the likely-late target colour and/or showed greater motor preparation for the likely-late response throughout trials. The reason for this is unclear. Since the response hands and colours assigned as likely-early and likely-late were counterbalanced across participants, it is unlikely that this benefit was due to response hand ability or low-level stimulus features.

Although no significant interactions were found, performance benefits for likely-late over likely-early targets were *numerically* larger when targets appeared late compared to early, particularly in the FMT and MT conditions, and to a lesser extent in the FT condition (Figure 3.4). These trends suggest that participants may have increasingly guided their attention toward the likely-late target colour and/or prepared the likely-late response as a trial progressed. This pattern aligns with my hypothesis that participants would adaptively modulate their behaviour during trials based

on learnt regularity-based predictions. However, given that these interactions did not reach statistical significance, it cannot be concluded that participants engaged in this behaviour.

3.5 General Discussion

When all targets followed assigned regularities during learning, performance benefits were found for targets following feature-temporal, motor-temporal, and feature-motor-temporal regularities, relative to purely temporal regularities. These findings suggest that participants' performance benefitted from learning to predict not just *when* a target was likely to appear, as target onset times were equated in the baseline condition, but from predicting targets' temporally likely colour and/or response. These benefits were selective to late-onset targets for feature-temporal and feature-motor-temporal regularities, but not for motor-temporal regularities.

This result regarding *feature-motor-temporal* regularities extends the findings of Chapter 2 by suggesting that these regularities can truly *enhance* DVS performance, when performance is compared to a more neutral baseline that does not conflate benefits with costs due to regularity violations. Further, this benefit was found in a modified task context from those in Chapter 2, with different timings, stimuli, and response decision criteria. This finding is therefore a valuable confirmation, given that effects of temporal expectations can be highly sensitive to task design (Seibold et al., 2023; van Ede et al., 2020), and underscores the potential utility of feature-motor-temporal regularities in guiding search across varied contexts.

The findings of distinct performance benefits for *motor-temporal* and *feature-temporal* regularities within directly comparable tasks is noteworthy. It suggests that both forms of temporal regularity can be independently learned and used to improve DVS performance. This extends the findings of Thomaschke et al. (2016), who provided indirect evidence that concurrently learned feature-temporal and motor-temporal regularities give rise to separable temporal expectations for

target features and responses. In addition to investigating these regularities in a free-viewing DVS context, and testing for performance benefits relative to a neutral baseline, the present study manipulated the presence of these regularities between rather than within participants. This between-subjects design eliminated potential interference or transfer between specific temporal predictions across domains, enabling a more direct assessment of performance benefits associated with each type of regularity in isolation.

The finding that *feature-temporal* regularities led to enhanced performance without temporally predictable motor responses is of particular interest. This result suggests that, while temporal preparation of specific motor responses is often implicated in effects of temporal expectations (Salet, Kruijne, Rijn, et al., 2022; Seibold et al., 2023; Thomaschke & Dreisbach, 2013), it is not essential for feature-temporal predictions to benefit behaviour. This complements Echeverria-Altuna et al.'s (2024) and Gao et al.'s (2025) findings of performance benefits associated with targets of particular colours that appeared at predictable, versus unpredictable, times during trials, under spatial and motor uncertainty.

The present findings extend this prior work in two ways. Firstly, feature-based guidance in the present study needed to operate over a wider spatial range and more selectively, prioritising targets over distractors. Secondly, participants in the prior studies (Echeverria-Altuna et al., 2024; Gao et al., 2025) were instructed to identify a target of one specific colour per trial. Temporal tuning of feature-based attention in these studies may therefore have resembled a dynamic sharpening of goal-based guidance toward one particular target colour at its likely time. By contrast, participants in the present study needed to identify any pink *or* blue target in each trial, requiring attention to be guided toward two colours per trial. Any tuning of feature-based attention in the present study therefore more likely resembled a dynamic re-weighting of goal-based guidance to two target

colours, rather than one, towards whichever was temporally likely (as found in Chapter 2 Experiment 2: Feature-Temporal Capture).

The present task design successfully separated feature-temporal regularities from predictable responses by specific effectors, but not from responses entirely. Participants were required to make speeded motor responses shortly after each target onset, and it is very likely these responses were preceded with saccades towards the targets themselves. Thus, participants could still have predicted the times when *some* motor action would be required. Previous studies finding benefits for feature-temporal regularities without concurrent effector-specific motor-temporal regularities also required speeded responses to targets (Echeverria-Altuna et al., 2024; Gao et al., 2025; Thomaschke et al., 2016). It is therefore unclear whether feature-temporal regularities can guide behaviour without *any* motor response being temporally tied to the target appearances and providing additional scaffolding. Thomaschke et al. (2013), however, found that response-related temporal expectations only improved performance if tied to specific effectors, suggesting more general motor predictability may not be useful here. Investigating feature-temporal guidance during DVS without any time-locked motor activity, for example by using delayed reports in a task performed while maintaining fixation (similarly to some temporal cueing tasks such as Chauvin et al., 2016, Vangkilde et al., 2012, and Zokaei et al., 2021), could help clarify this. However, such an approach would change task demands, e.g., by adding a memory load, which may disrupt regularity learning. Further, as real-world visual search typically involves some motor action after finding a target (e.g., a saccade or a reach), it's worth questioning whether removing all motor responses at predictable target timings is ecologically relevant.

In this experiment, performance benefits for feature-temporally predictable targets were observed even though the temporally predictable target feature (colour) did not define response. This result is in contrast to Thomaschke et al., (2016)'s suggestion that a temporally predictable target

feature needs to directly inform target response for FT regularities to benefit performance. That said, colour was still task relevant here in that it (partially) differentiated targets from distractors, as was the case in Echeverria-Altuna et al. (2024) and Gao et al. (2025). It would be interesting to test whether a performance benefit for feature-temporal regularities would emerge in the present DVS task if non-target colours (i.e., green distractors) were removed. It is unclear whether participants would, more incidentally, learn to expect pink or blue targets at specific times during trials if selective goal-based attentional guidance toward these colours was unnecessary.

Though revealing, the present finding of a performance benefit for feature-temporal regularities regarding late-onset targets in the learning session was not statistically robust. In the main IES analysis, evidence for the FT vs. N benefit was classed as anecdotal by a Bayes factor analysis. Moreover, supplementary analyses of hits and RTs individually found no statistically significant benefits for feature-temporal regularities, although both showed non-significant trends indicating benefits for late-onset feature-temporally predictable targets compared to baseline (Supplementary Figure 7.10 and Supplementary Figure 7.11). These weak results may be indicative of smaller performance benefits for temporal predictions when motor predictability is absent.

It is worth considering here that, as suggested by the analyses in Supplementary Figure 7.10 and Supplementary Figure 7.11, feature- and motor-based temporal predictions may have distinct impacts on different components of performance. Specifically, motor-temporal regularities exerted greater influence on RTs than feature-temporal regularities, and appeared to affect RTs more than accuracy. This pattern may reflect that temporal preparation for motor responses is closely linked to response speed, due to its direct involvement in motor planning and execution. In contrast, feature-temporal predictions may act on attentional and perceptual systems that are less directly connected to response execution, thereby influencing RTs more indirectly and potentially leading to more variable or reduced effects. These distinctions also highlight potential limitations of using IES as a

compound measure of performance when experimental manipulations may differentially affect its individual components.

Another explanation for the marginal findings regarding the FT condition in the present study is insufficient statistical power. Although the sample size was calculated to detect medium-sized effects between conditions with 80% power (see Participants), the observed effect for the FT versus N benefit was smaller (d = 0.27). Since the baseline condition also contained a high degree of temporal regularity, with early and late target onset times predictable across trials, the potential size of performance benefits was likely reduced compared to a baseline with temporally unpredictable targets. This, combined with increased variability within and between participants due to conducting the study online (Rodd, 2024), and with limited statistical power, may have hindered the reliable detection of performance benefits. Future in-person research with larger samples is warranted to more robustly assess the potential of isolated feature-temporal regularities to benefit DVS performance.

A remaining question is whether feature-temporal predictions can be used adaptively to *suppress* temporally likely but irrelevant features during dynamic visual search. It is unclear whether this occurred in the FT condition of the present study. While the learning session analysis found performance benefits for the FT versus N condition, the extent to which these benefits may have arisen from an enhancement of guidance toward the temporally likely target colour, versus guidance away from the temporally unlikely target colour is unclear. So far, the experiments in this thesis have addressed target-based feature-temporal regularities. However, a case in which temporally tuned suppression of features could be particularly useful during DVS is if distractors appeared with feature-temporal regularity. This is investigated in Chapter 4.

Turning to the testing session, the lack of significant performance differences between temporally likely and unlikely targets was unexpected. One interpretation is that the performance

benefits observed for conditions in the learning session did not reflect participants having used regularities to guide their behaviour over time, but instead resulted from an unidentified design confound or inherent differences between participant groups. Perhaps a more likely explanation is that the testing session analysis lacked sufficient statistical power to detect effects. The sample size had over 95% power to detect a medium-sized within-subjects effect (see Participants). However, due to constraints associated with testing participants online (i.e., high rates of fatigue during long and attentionally demanding experiments), the number of trials per level was relatively low. For each participant, data from 24 valid and 12 invalid responses were available for early-onset targets, and 16 valid and 8 invalid responses for late-onset targets, before data cleaning. These limited trial counts, combined with the added data variability associated with running the task online, may have led to unstable averages and increased the influence of outliers, making it harder to detect true effects. It is also possible that participants had used regularities to dynamically modulate their behaviour during learning session trials but quickly adapted to temporally unlikely targets in the testing session, minimising performance costs.

Although no statistically significant effects of temporal tuning emerged in the testing session, there were non-significant trends suggesting performance benefits for temporally likely targets in each of the MT, FMT, and, to a lesser extent, FT conditions. Strikingly, the temporal specificity of these trends closely aligned with the performance benefits found for each condition in the learning session. For the MT condition, numerically more efficient performance for temporally likely versus unlikely targets was found for both early and late targets in the testing session, matching the significant performance benefits found for the MT versus N condition for both early and late targets in the learning session. For the FT and FMT conditions, numerical benefits for temporally likely targets in the testing session were restricted to the late onset time, aligning with the late-onset-specific performance benefits found for these conditions during learning. While testing session trends did not

reach significance, their temporal mirroring of the learning session effects supports the view that performance benefits during learning arose from participants using regularities to guide their behaviour over time.

The differences in the temporal specificity of effects between conditions is intriguing. While regularities appeared to influence behaviour for all targets in the MT condition, this was restricted to late targets in the FT and FMT conditions. This raises questions about differences in how temporal tuning may operate in perceptual and motor domains. The observed differences in temporal specificity between the MT and FMT conditions are especially curious, as the FMT condition included the same motor-temporal regularities as the MT condition but with additional, concurrent feature-temporal regularities. This suggests that learnt predictions based on feature-temporal regularities may have been dominant in determining the temporal-specificity of behavioural effects in this task, preventing them from occurring early during trials. These findings warrant further investigation and underscore the need to consider the separate contributions of temporal tuning in perceptual and motor domains on DVS behaviour, not only in terms of *if* a performance benefit occurs, but also *when*.

Finding that regularity-based performance benefits for the FT and FMT conditions were specific to late rather than early targets was unexpected. Prior studies have found stronger effects of temporal expectations on performance at shorter (earlier), rather than longer (later) intervals after trial onset (e.g., Coull et al., 2000; Heideman et al., 2018; Miniussi et al., 1999; Xu et al., 2023, 2025). Similarly, both experiments in Chapter 2 found performance benefits for feature-motor-temporally likely versus unlikely targets that were specific to early-onset targets. Several design differences from Chapter 2, such as the task being online, trial timings, stimulus design, and response-related decision criteria, may have caused this reversal in temporal specificity through reducing participants' engagement or attentional readiness early during trials.

A perhaps more critical difference between the present task and those in Chapter 2 was the lack of target-absent trials. This meant that onset time was linked to certainty about target appearance in the present study: if a target had not appeared early, participants could be certain one would appear late. Expectations about *if* a target will occur and expectations about *when* a target will occur are thought to be independent (Grabenhorst et al., 2021), but may have interacted here. It is possible that participants here needed to be certain that a target would appear imminently in order to utilise predictions about its temporally likely colour (FT) and response (FMT). Future work could test whether introducing target-absent trials in this task reduces the late-specificity of, or eliminates entirely, performance effects for FT and FMT regularities. Overall, this finding highlights how sensitive the expression of effects of temporal regularities can be to DVS task design.

3.6 Conclusion

This chapter used a novel variation of the DVS tasks from Chapter 2 to independently manipulate the presence of feature-temporal and motor-temporal regularities between participants. The findings suggest that both types of regularity can be learned and used independently, as well as in combination, to (partially) benefit search performance relative to their absence. This work underscores the importance of considering how learnt temporal predictions may shape both perceptual and response processes during DVS, and highlights the sensitivity of such effects to variations in task design.

4 Investigating Feature-Temporally Predictable Distraction

4.1 Abstract

In addition to orienting attention towards relevant targets, successful visual search requires that observers avoid engaging with distractors. Previous research has demonstrated that regularities across various distractor dimensions can aid in suppressing irrelevant stimuli. However, it remains unclear whether such benefits can extend to feature-temporal distractor regularities in dynamic settings. This chapter addresses this gap using a novel online, tablet-based dynamic visual search task. Specifically, it investigates 1) how transient distraction affects performance at different times within trials and 2) whether temporal regularities in distractor colour can benefit search. Coloured circles appeared transiently in unpredictable locations throughout temporally extended trials. Participants were instructed to collect (tap on) as many target circles as possible while avoiding distractors. Distractors were defined by two specific hues and appeared in waves of three of the same colour, either early or late within trials. During learning, each distractor colour consistently appeared at a predictable time (early or late), then, during testing, these regularities were occasionally violated. First, I confirmed that distractor appearances impaired performance, finding costs for targets appearing both during and after distraction. I then tested for benefits of feature-temporal distractor predictability by comparing performance when distractor colour was temporally likely versus unlikely in the testing phase. I additionally compared performance between targets in adjacent hues to temporally likely and unlikely distractor colours during the learning phase. Unexpectedly, while participants appeared to learn the regularities, distractor predictability did not significantly affect performance during the distraction period itself. Instead, predictions, particularly those related to

early distraction, had more downstream effects on behaviour. Specifically, recovery from early distraction was better when early distractors appeared in the colour consistent with the learnt regularity, compared to when they appeared in the colour typically associated with a late onset. Additionally, performance was worse for early targets that resembled the temporally expected (likely-early) distractors than for those resembling the temporally unexpected (likely-late) distractors. This chapter highlights the importance of considering how both timing within the search episode and temporal predictions shape the handling of temporary distraction within dynamic visual search contexts.

4.2 Introduction

Effective visual search not only involves guiding attention toward goal-relevant targets, but also requires that attention be steered away from irrelevant, distracting information. How distractors are successfully suppressed or ignored has been a central topic in recent visual search research (for an overview, see Carlisle, 2023; Gaspelin & Luck, 2018; Geng, 2014; Liesefeld et al., 2024; Slagter & van Moorselaar, 2021; Theeuwes, 2023). As with most visual search literature, the vast majority of studies on distraction have focussed on search within static displays in which participants maintain central fixation (see also Wöstmann et al., 2022). This raises important questions about how distractors are avoided in dynamic, free-viewing search tasks that more closely resemble real-world contexts, and how distractor handling may be shaped by temporal regularities within such environments. Chapters 2 and 3 provided evidence that learnt feature-temporal predictions about targets can dynamically tune attentional prioritisation of target features. The present chapter asks whether similar regularity-based tuning can guide attention away from temporally likely distractor features.

Distractor handling can take various forms. One mechanism is top-down suppression arising from explicit instruction about where (Chao, 2010; Munneke et al., 2008; van Zoest et al., 2021), or in what colour (Addleman & Störmer, 2022; Arita et al., 2012; Carlisle, 2023; Chidharom & Carlisle, 2024) distractors are likely to appear. Top-down colour-based suppression has been proposed to operate via negative templates, internal representations that guide attention away from expected distractor features. However, negative templates are only effective under certain task conditions (Carlisle, 2023) and may lead to reactive distractor ignoring rather than proactive suppression (Addleman & Störmer, 2022).

Another, perhaps more robust, mechanism of distractor handling is the use of distractor-based regularities. Most studies in this area have examined the learnt suppression of a single salient distractor, typically using an additional-singleton task design (Theeuwes, 1992). In this design, participants search for a singleton shape target (e.g., a green circle among green diamonds). On some trials, a colour singleton distractor appears (e.g., a red diamond). This salient distractor typically captures attention and delays target identification. Numerous studies have found that attentional capture by a salient distractor can be attenuated when it appears in a predictable location across trials (e.g., Allenmark et al., 2024; Britton & B. A. Anderson, 2020; de Waard et al., 2022; Di Caro et al., 2019; Goschy et al., 2014; Sauter et al., 2018; B. Wang & Theeuwes, 2018), with participants demonstrating proactive suppression at this high-probability location (Ferrante et al., 2022; Huang et al., 2023; Richter et al., 2025; although see Geng & Duarte, 2021 for continued debate regarding the timing of suppression).

Studies have also demonstrated that predictable non-spatial distractor features can be suppressed across search trials, independent of spatial predictability effects. In additional-singleton tasks, participants will rapidly suppress salient distractors that repeatedly appear in a high-probability colour, reducing their attentional capture (Golan & Lamy, 2022; Stilwell et al., 2019). Further studies

have shown that, even in displays containing multiple stimuli in each of multiple colours (i.e., where distractors are not salient singletons), participants can learn to guide their attention away from stimuli in a predictable distractor colour, ultimately facilitating target identification (Addleman & Störmer, 2023; Savelson & Leber, 2024).

Relatively few studies have investigated the effects of *temporal* expectations on handling distraction (Seibold et al., 2023). In a singleton visual search task, Lamy (2005) found that attentional capture by a salient 'irrelevant onset' distractor preceding the target could be overridden when the interval between distractor and target onsets was fixed. Outside of visual search, Gresch and colleagues (2021) showed that distractors presented during the retention period of a working memory task had a less detrimental effect on performance when they appeared at a predictable time. Further, van Ede et al. (2018) found that cued temporal anticipation of a target delayed interference from a temporally adjacent distractor on the visual representation of target features. Moreover, Wendt and Kiesel (2011) associated the level of target-distractor conflict in an Eriksen flanker task (high vs. low) with foreperiod duration (short vs. long). Greater flanker interference was observed at the foreperiod associated with low conflict, suggesting that participants had modulated their attentional control based on the temporally expected level of interference.

The effects of temporal regularities operating contingently with regularities in other domains on distraction handling remain largely unexplored. In a 2021 study, Xu and colleagues examined the effects of spatiotemporal regularities on the suppression of a salient distractor in an additional-singleton task. The static search display was presented after either a short or long foreperiod. The salient distractor appeared at one location with high probability following the short interval, and at a different location with high probability following the long interval. They found that the likely-late distractor location was suppressed at the long, but not the short foreperiod, consistent with participants having dynamically tuned their location-based suppression to the task regularities. To

date, no studies have investigated whether learning distractor-based *feature*-temporal regularities can adaptively tune *feature-based* distractor handling over time. The present study addresses this question using an online, tablet-based dynamic visual search (DVS) task.

The DVS task was similar to those in Chapters 2 and 3, the primary difference being the relative prevalence of targets and distractors. Here, most stimuli in a trial were targets while distractors appeared in waves of three presented either never, only early, only late, or both early and late during a trial. Stimuli were coloured circles in several hues, with distractors defined as two specific colours. Critically, distractors in one colour were most likely to appear early, while distractors in the other colour were most likely to appear late. During an initial learning session, each distractor colour always appeared at its likely time. In a following testing session, some distractors appeared at their unlikely time. Participants were instructed to tap on targets and to avoid distractors.

By filling trials with temporally unpredictable targets, this study was able to probe behaviour continuously in a busy environment where distractor regularities occurred among intervening events. The central aim was to investigate whether participants could learn distractor-based regularities in such an environment to mitigate the costs of feature-temporally expected distraction. This approach enhances ecological validity compared to studies using traditional, static search displays. Importantly, the continual appearance of targets also allowed for behavioural measurement across numerous timepoints per trial, providing a richer temporal profile than tasks sampling only one or two responses per trial, such as that in Chapter 3. This design also allowed for the examination of any lasting effects of early distraction on later performance in the same trial, something rarely explored previously during visual search (though see Liesefeld et al., 2017; Sauter et al., 2021; Wang et al., 2019). This methodology bridged the temporally resolved insights provided by the eye-tracking and EMG measures in Chapter 2 with the efficiency and scalability of online data collection used in Chapter 3. The task adds to a growing body of recent dynamic, multi-target foraging-style visual search tasks in

which participants click or tap on targets, emulating real-world reaching behaviour (Boettcher & Nobre, 2025; Grössle et al., 2023; Shalev et al., 2024; Tünnermann et al., 2021; Tünnermann & Schubö, 2025).

Consistent with the recommendations of Wöstmann et al. (2022) for studying distraction, I first confirmed that the distractors did distract participants, and that this was measurable via deficits in target performance. I then examined whether the feature-temporal regularities had influenced behaviour. Firstly, I compared performance when distraction appeared in the temporally likely or temporally unlikely colour during the testing session. To pre-empt the results, performance for targets that overlapped temporally with distractors did not differ depending on whether the distractors' colour was temporally likely or unlikely. However, when distraction occurred early, temporally unlikely distractors had a worse effect on performance across the entire trial, indicating that participants recovered more effectively from feature-temporally predictable distractors. In addition, I investigated whether participants avoided targets similar in colour to the distractors, and how this changed over time depending on which distractor colour was temporally likely. Here, targets similar to the likely-early distractor colour were avoided more than those similar to the likely-late distractor colour specifically at *early* times during distraction-absent learning trials.

These unexpected yet interesting findings demonstrate that, while participants may have formed learnt feature-temporal predictions about distractors, behavioural consequences of these predictions mainly emerged in the absence of visible distraction. This chapter showcases the potentially limited ability of distractor-based feature-temporal regularities to benefit DVS performance, while underscoring the importance of examining the secondary effects of distraction on performance over time.

4.3 Methods

4.3.1 Participants

Experimental procedures were reviewed and approved by the University of Oxford Medical Sciences Interdivisional Research Ethics Committee. Participants were recruited via Prolific (www.prolific.co). All participants were aged between 18 and 40 years and self-reported normal or corrected-to-normal vision (including colour vision), fluency in English, no current mental health conditions, and no use of psychoactive medication. Participants were also required to have completed at least five previous studies on Prolific, with at least 90% of their previous submissions approved.

All participants gave informed consent and were compensated at a base rate of approximately £10 per hour, based on an expected completion time of 55 minutes. An additional payment of up to £2.50 was awarded to participants whose average score in the task exceeded 80% (see Feedback and Scoring). This bonus payment scaled linearly, from £0.50 for a score of 80% to £2.50 for 100%, with an average bonus of £0.63 (*SD* = 0.71) across participants in the final sample.

The final sample consisted of 80 participants (33 female, 46 male, 1 other; mean age = 28.20 ± 6.34 (*SD*)). Sample size was determined a priori using a G*Power 3.1 analysis (Faul et al., 2007) based on an effect size of $d = 0.32$. This effect size is a 30% reduction of the observed effect size in Chapter 2 Experiment 2 ($d = 0.46$) regarding performance for feature-(motor)-temporally likely versus unlikely targets. A reduced effect size was used as I anticipated effects for learnt predictions may be smaller when they related to distractors rather than targets. A sample size of 80 had over 80% power to detect an effect of this size in a two-tailed repeated-measures *t*-test ($\alpha = .05$).

4.3.2 Apparatus

All participants completed the study using their own touchscreen tablet. Note that it was not permitted to complete the experiment using a mouse or trackpad. Participants were asked to sit

approximately 30 cm from the screen, to orient the device in landscape, and to set the screen brightness to maximum. The experimental script (available at https://osf.io/jbd86/files) was programmed using PsychoJS (PsychoPy v2023.2.3; Peirce et al., 2019) and hosted online using Pavlovia (www.pavlovia.org).

4.3.3 Dynamic Visual Search Task

Stimuli. The search display consisted of target and distractor stimuli (plain coloured discs; Figure 4.1A) that appeared transiently at various times and locations over a static 1/F greyscale noise background (Figure 4.1B). A video demonstration of a trial is available at https://osf.io/jbd86/files. The background image measured 15.00 cm x 9.00 cm across all devices. These measurements were chosen to fit within the smallest standard tablet screen. A unique background image was pre-generated for each trial using MATLAB (MATLAB v2020a; The MathWorks Inc., 2020), and images were assigned to trials randomly.

Stimuli were filled circles with a diameter of 0.79 cm (approximately 1.5 DVA, assuming a viewing distance of 30 cm). Each stimulus appeared in one of eight colours, selected as equidistant points around a circle in the *ab* plane of the CIELAB colour space (L*, a*, b*) with lightness fixed at 75 (Figure 4.1A). For all participants, distractors appeared in the same two colours, located opposite each other on this circle: 'purple' (LAB(75.00, 21.53, -21.53); stimulus *A* in Figure 4.1A) and 'green' (LAB(75.00, -21.53, 21.53); *E*). Targets appeared in the remaining six colours: 'pink' (LAB(75.00, 30.45, 0.00); *B* in Figure 4.1A), 'orange' (LAB(75.00, 21.53, 21.53); *C*), 'gold' (LAB(75.00, 0.00, 30.45); *D*), 'turquoise' (LAB(75.00, -30.45, 0.00); *F*), 'sky blue' (LAB(75.00, -21.53, -21.53); *G*), and 'cornflower blue' (LAB(75.00, 0.00, -30.45); *H*). That is, participants were tasked with tapping on all coloured discs, except the distractors.

Distractors always appeared in waves of three of the same colour. Given that several stimuli could appear concurrently at different locations during a trial, participants may frequently miss the

appearance of a single distractor if their attention is with a target in a distant area of the display. If so, this would hinder their ability to learn the distractor regularities (D. H. Duncan et al., 2025). Having three distractors appear at a similar time therefore increased the probability of participants attending to at least one distractor in a given trial.

Each trial contained 19 targets. Five of the six possible target colours each appeared three times during a trial, while one target colour was randomly chosen to appear four times. In addition to the 19 targets, a trial could contain zero, one, or two waves of distraction, with zero, three, or six distractors appearing overall, respectively. Accordingly, the total number of stimuli per trial ranged from 19 to 25.

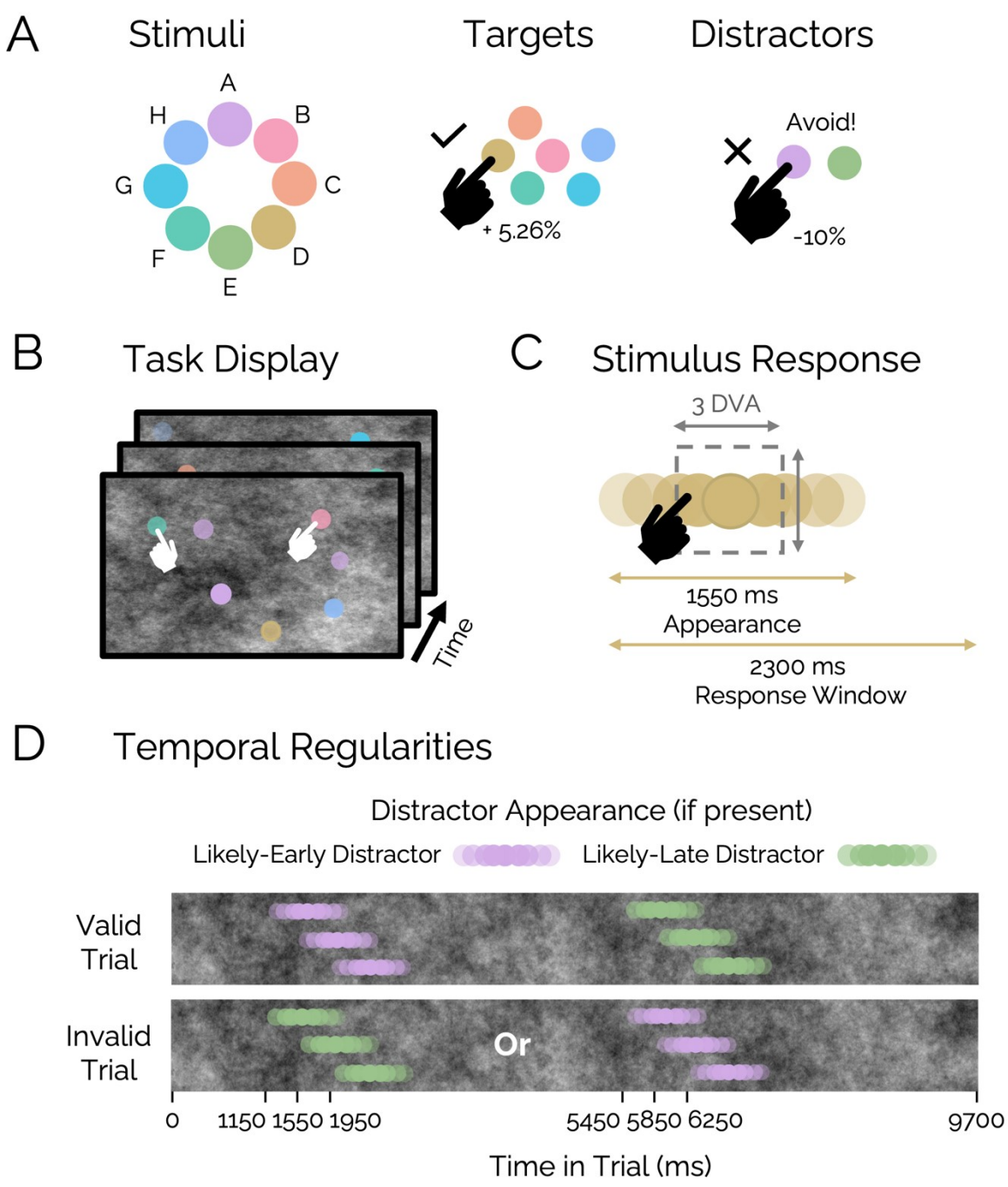


Figure 4.1. DVS schematic. **(A)** The eight stimuli, with six target colours and two distractor colours that were the same for all participants. For each target collected, the score for that trial increased by 5.26% (1/19th). For each distractor collected, the score decreased by 10%. **(B)** Illustration of a DVS trial. Stimuli faded in and out of a static noise background at different times and locations. Participants were instructed to tap on targets using both hands and to avoid distractors. A video demonstration of a trial can be found here: https://osf.io/jbd86/files. **(C)** For taps to be 'on-stimulus', they needed to fall within a 3 x 3 DVA square centred on the stimulus within 2300 ms of its onset. **(D)** Example likely-early and likely-late distractor colours and schematic of distractor timings in valid trials

(top row) and invalid trials (bottom row). Distractors appeared in waves of three of the same colour, in random locations. Distractors appeared either early (onset times 1150 ms, 1550 ms, and 1950 ms) or late (5450 ms, 5850 ms, and 6250 ms). In general, distraction waves during trials could occur either early, late, both early and late, or never. During invalid trials, only one distraction wave occurred, early or late.

General Timings. DVS trials lasted 9700 ms. Each stimulus faded in from zero to a maximum opacity of 0.9 over 400 ms, remained at maximum opacity for 750 ms, then faded back out over 400 ms. The total duration for which a stimulus' opacity was greater than zero was therefore 1550 ms (Figure 4.1C). Stimulus onset time was again defined as the time when a stimulus first began fading in, relative to the trial start.

Distractor Timings (Predictable). Within a wave of distraction, three distractors appeared with staggered onset times 400 ms apart, such that their appearances overlapped. Distraction could occur either early or late during a trial. In early distraction waves, distractors onset at 1150 ms, 1550 ms, and 1950 ms. During late distraction waves, they onset at 5450 ms, 5850 ms, and 6250 ms. See Figure 4.1D for a schematic of distractor timings within trials.

Across all trials, distractors were equally likely to appear early or late, and to be purple or green. However, distractor colour was predictable based on timing: one *'likely-early'* colour was more likely to appear early, while the other, *'likely-late'* colour was more likely to appear late (see Figure 4.1D for an example). The exact probability of each colour occurring at each time depended on the experimental session (see Learning and Testing Sessions). The assignment of each distractor colour as likely-early or likely-late was counterbalanced across participants. Participants were not informed of any temporal regularities until the experiment had ended.

Targets Timings. Targets were temporally unpredictable. On every trial, each of the 19 targets was pseudo-randomly assigned an onset time between 0 ms and 7400 ms, with the constraint that no two targets could onset within 200 ms of one another. This assignment meant that no stimuli

were visible at the very start or end of each trial and, as such, participants theoretically had an equal amount of time to respond to each target (see Collecting Targets and Avoiding Distractors).

Stimulus Locations. All stimuli were spatially unpredictable across trials. On each trial, 25 locations were pseudo-randomly generated so each stimulus could be assigned a unique location. To generate these locations, the display was first divided into 25 equally-sized cells separated by borders. These cells were not visible during trials, but were used solely for location generation. One (x, y) pixel coordinate pair was randomly selected from within each cell. Coordinate pairs were then randomly assigned to stimuli without replacement, regardless of whether stimuli were targets or distractors, and dictated the location of the stimulus centre. On trials with fewer than 25 stimuli, some cells contained no stimuli. Borders between cells were sized to prevent stimuli from overlapping with one another or extending beyond the background. Specifically, the borders were such that centre of each stimulus was at least 2.5 DVA from any other stimulus centre, and at least 1 DVA from all background edges. Locations were fixed as stimuli faded in and out.

Collecting Targets and Avoiding Distractors. Participants were instructed to collect as many targets (referred to as *good berries* in the task instructions) as possible on each trial, as quickly as possible, and to avoid collecting distractors (*poisonous berries*). Participants were not told if, or when, distractors would appear on a given trial. To collect a stimulus, participants needed to tap on it within 2300 ms of its onset (Figure 4.1C). This response window extended 750 ms beyond stimulus offset. Participants were told that they should use both hands to make responses. A tap was registered as on-stimulus if it fell within a square region measuring 3 x 3 DVA centred on the stimulus (Figure 4.1C).

Feedback and Scoring. At the end of each trial, participants were shown a score indicating the percentage of targets they had collected on that trial. Each target collected increased the score by 5.26% ($1/19^{th}$). If participants had collected any distractors, they were informed, reminded of which colours to avoid, and given an adjusted score. To motivate participants to avoid distractors,

the scoring system imposed a 10% deduction for each distractor collected, approximately twice the reward for collecting one target (Figure 4.1A; similar to Tünnermann & Schubö, 2025). If a participant collected 80% of targets but also collected two distractors, their adjusted score would be 60%. The adjusted scores were averaged across trials to calculate each participant's bonus payment.

Learning and Testing Sessions. All participants completed six experimental blocks, each with 40 DVS trials. These were divided into an initial four-block '*learning session',* followed by a two-block *'testing session'*. Participants were not informed of this division. Regardless of session, each block included 10 trials with no distraction, 10 trials with both early and late distraction, 10 trials with only early distraction, and 10 trials with only late distraction, randomly intermixed.

All learning trials were '*valid'*, meaning that any distractors that appeared followed the participant's assigned feature-temporal regularities. For example (Figure 4.1D), a participant might consistently experience purple distractors early and green distractors late.

In the testing session, distractor colour was less temporally predictable. On trials with a single distraction wave, feature-temporal regularities from the learning session were preserved in half of the trials (valid trials) and reversed in the other half ('*invalid'* trials). During an invalid trial for the example regularities in Figure 4.1D, early distractors would appear in green and late distractors in purple. All trials containing two distraction waves remained valid. This reinforced the previously learnt associations and did not impact the analysis of valid versus invalid distractors, since this was limited to performance in trials with a single distraction wave (see Variables of Interest). As a result, across the testing session, 75% of all distraction waves upheld the regularities from the learning session while 25% violated them. Regardless of session or trial type, all three distractors within a wave always shared the same colour.

4.3.4 Procedure

Participants first provided informed consent and demographic information via *Qualtrics* (www.qualtrics.com), before being redirected to *Pavlovia* (www.pavlovia.com) to complete the DVS task. They were instructed to complete the task in a quiet place where they would not be disturbed, and not to listen to music. So that stimuli could be presented in approximately the same size across devices, I first measured the pixel scale of each participant's screen using a touchscreen-adapted version of the *ScreenScale* routine for PsychoPy (Morys-Carter, 2023). This required participants to resize a digital rectangular image to match the dimensions of a standard ID or bank card.

After screen scaling, participants read the task instructions and viewed a video demonstration of a trial. Distractors were not mentioned at this stage. Participants then completed two distractor-absent practice trials to become familiar with collecting targets. Afterwards, participants read further instructions that informed them of the distractors and the penalty for collecting them, as well as details of the bonus payment calculation.

Participants then completed a short training session to help them learn to distinguish targets from distractors. On each of 20 training trials, one stimulus was presented at the centre of the screen at maximum opacity for two seconds. Participants were instructed to tap the stimulus if it was a target ('good berry'), or withhold if it was a distractor ('poisonous berry'). Each target stimulus was shown on two trials, and each distractor stimulus on four trials, in a random order. After each training trial, participants received feedback as 'Correct!', 'Incorrect! You hit a poisonous berry', or 'Incorrect! You missed a good berry'. If incorrect, they were reminded of which colours to tap and which to avoid. Participants needed an accuracy of at least 80% to continue, or else the training was repeated. On average, participants completed the training 1.05 times before progressing.

After training, participants completed the six experimental blocks of DVS trials. Each block lasted approximately seven minutes. Between blocks, participants could take breaks lasting up to five

minutes. At the end of each block, participants were shown their average score for that block (factoring in penalties) and, for all blocks except the first, how this score compared to that from the previous block.

4.3.5 Variables of Interest

Analysis served two main goals. The first was to examine how basic effects of distraction on performance manifested in this task, across time-in-trial and across blocks, without regard to the feature-temporal regularities. Data from the learning session were used to assess whether the appearance of distraction impaired target collection, and whether participants improved at prioritising targets over distractors with task exposure.

The second aim was to assess whether feature-based distractor handling was temporally tuned to the task regularities. I investigated this from two angles. Firstly, I tested for performance benefits when distractor colours appeared at valid versus invalid times during the testing session. Secondly, I examined whether performance detecting targets of different colours changed over time during target-absent learning session trials, depending on the similarity of a target's colour to the temporally likely distractor colour.

Basic Effects of Distraction on Performance. I first used target hit rates and RTs from the learning session to confirm that distractors did, in fact, distract participants and measurably disrupt their performance in collecting targets. This was essential as, if participants could ignore distractors from the outset, they likely would not have engaged with them enough to learn their feature-temporal regularities. Further, if even basic distraction effects were not detectable via target performance, then these measures would be unsuitable for investigating more subtle modulations of distraction effects caused by feature-temporal predictions.

I also investigated whether participants improved at handling distractors over the learning session using target hits, target RTs, and *d'* scores. Evidence of improved performance would be consistent with participants having learnt to handle the waves of distraction more effectively.

Target Hits and RTs. Target hits and RTs served as dependent measures of task performance and were analysed separately. Decreases in hit rates and increases in RTs were taken as proxy indications of distraction. Hits were a binary measure indicating whether a target had been tapped on within the response window (hit; 1), or not (0). Hit criteria are illustrated in Figure 4.1C. RTs were the time, in ms, between target onset and the first on-target tap that resulted in a hit. Taps on targets made after the response window (i.e., RT > 2300 ms) were not classed as hits.

I analysed the effects of three within-subject independent variables on hits and RT. The first was *distraction timing* (none, early, or late), a categorical variable indicating whether a trial contained no distraction, only an early distraction wave, or only a late distraction wave. Distraction-absent trials served as the baseline for comparisons with early and late distraction trials. Trials that contained both early *and* late distraction were not analysed, allowing the effects of distraction occurring early versus late to be investigated without one influencing the other.

The second independent variable was *target onset time*. For initial exploratory plots, onset times (0-7400 ms) were treated as continuous to visualise any dynamic, enduring effects of distraction on performance during a trial. For statistical analysis, however, onset times were grouped into two categorical levels: *target onset window* (early or late). Target onset windows lasted 2750 ms and were centred around, and encompassed, the corresponding distraction wave (early vs. late). The early onset window included targets with onsets between 175 ms and 2925 ms, while the late onset window began at 4475 ms and lasted until 7225 ms. Only targets with onsets in one of these windows were analysed. The appearance of each 'early' target overlapped temporally with at least one early distractor. This overlap could be partial, with some early targets fading in before any distractors were

visible, and others remaining visible after all early distractors had disappeared. No early target overlapped temporally with any late distractor. The opposite was true for 'late' targets.

I hypothesised that the effects of target onset window and distraction timing would interact. If participants were distracted by the distractors, and this was measurable via target performance, then hit rates and RTs would be selectively impaired for targets that appeared at the same time as distractors. I expected lower hit rates and slower RTs for early targets in trials with early distraction, and for late targets in trials with late distraction, compared to early and late targets in distraction-absent trials, respectively.

I also hypothesised that these effects may depend on a third independent variable: learning *block number* (1-4). If participants had learned to better handle distraction over the learning session, then I expected that any impairments in hits or RT under distraction would be less pronounced in the final learning block than the first.

d'. In addition to assessing whether distraction effects on hits and RTs decreased across blocks, I directly investigated whether participants' sensitivity to targets *over distractors* improved during the learning session. Here, *d'* was the dependent measure, as it reflects both target hits and distractor false alarms. It was calculated as the difference between the standardized (z-scored) hit rate and false alarm rate, with the 1/2N rule applied to adjust for extreme values (Hautus, 1995). The criteria for a distractor false alarm matched that for a target hit (Figure 4.1C).

I compared *d'* scores across stimulus *onset window* (early vs. late) and learning *block number* (1-4), within participants. For each participant, *d'* scores were calculated for each combination of onset window and block, resulting in eight scores per participant (corresponding to the points in Figure 4.2E). For the early onset window, *d'* was calculated using the hit rate for early-onset targets (175-2925 ms onset) and the false alarm rate for early distractors, all from early distraction trials. For

the late onset window, *d'* was calculated using the hit rate for late targets (4475 – 7225 ms onset) and the false alarm rate for late distractors, all from late distraction trials.

I hypothesised that, if participants improved at handling distractors, then *d'* would increase across the learning session. I made no specific predictions regarding onset window.

Evidence for Learning the Feature-Temporal Distractor Regularities. *Testing Session: Comparing Feature-Temporally Likely Versus Unlikely Distraction.* This analysis tested for performance benefits when distraction appeared in the temporally likely versus unlikely colour. Only trials containing one distraction wave, early or late, were analysed. I analysed both *d'* and target RTs. The *d'* scores provided a measure of participants' ability to collect targets while avoiding distractors across distraction types. However, if participants were highly skilled at the task, then they may not have missed targets or made false alarms even if distracted to a greater extent. I therefore also analysed target RTs as an additional measure of distraction.

d'. The *d'* analysis compared performance across two within-subjects independent variables: stimulus *onset window* (early vs. late, as defined above) and *distractor likelihood* (likely-early vs. likely-late). This analysis only included targets whose appearances overlapped temporally with at least one distractor, i.e., early targets from early distraction trials and late targets from late distraction trials. Distractor likelihood was defined based on the feature-temporal regularities in the preceding learning session, indicating whether a distractor colour was *likely-early* or *likely-late* for a given participant. For every participant, I calculated four *d'* scores, one for each combination of onset window and distractor likelihood (corresponding to the bars in Figure 4.3A).

I hypothesised that, if participants had used the feature-temporal regularities to dynamically suppress distraction of each colour during trials, then they would be less distracted and perform better under temporally likely distraction than temporally unlikely distraction. For early stimuli, I

expected *d'* would be highest for likely-early distractors, while *d'* for late stimuli would be highest for likely-late distractors.

RT. This analysis again considered RTs for targets whose appearances had overlapped temporally with distractors, i.e., early targets from early distraction trials and late targets from late distraction trials. RTs were compared across two within-subjects independent variables: target *onset window* (early vs. late, as defined above), and *distractor likelihood* (likely-early or likely-late).

I hypothesised that, if participants had used the feature-temporal regularities to guide their handling of distractors, then RTs would be faster for targets that appeared alongside temporally likely distractors compared to temporally unlikely distractors, i.e., that RTs for early targets would be fastest under likely-early distraction, while RTs for late targets would be fastest under likely-late distraction.

Learning Session: Considering Colour Similarity Between Targets and Distractors. *Hits and RT.* An unintended consequence of participants learning to avoid the two distractor colours may have been impaired performance for targets similar in colour to distractors. To investigate this, an initial, supplementary analysis compared hits and RTs for each type of distractor-similar target with those for 'neutral' targets (targets *G* and *C* in Figure 4.1A), the colours of which fell equally between the distractor colours. The results of this analysis are provided in Supplementary Figure 7.15, Supplementary Table 7.19 and Supplementary Table 7.20. Overall, performance was consistently worse for targets similar in colour to either the likely-early or likely-late distractor colour, across onset times and blocks. This suggests that suppression, or avoidance, of the distractor colours may have been imprecise and this inadvertently reduced attention to, or caused confusion with, similarly coloured targets.

Given this, if participants had used the task's regularities to dynamically tune their handling of each distractor colour, then performance should be most impaired for targets similar in colour to

the temporally likely distractor at a given time in trial. To test this, I analysed target hit rates and RTs during distraction-absent learning session trials. Distraction-absent trials ensured that any changes over time could not be attributed to actual distractor appearances, but instead should reflect participants' internal tracking of time. I focussed on learning session trials to avoid any effects due to temporally invalid distractors in the testing session.

I analysed the effects of three within-subjects independent variables on target hits and, separately, RTs: *target onset window* (early vs. late, as defined above), target *colour type* (likely-early similar vs. likely-late similar), and learning *block number* (1-4). In the results, I focus only on main effects and interactions involving *colour type*, as these were of primary interest.

Colour type here was a two-level categorical variable indicating whether targets appeared in a hue neighbouring the likely-early distractor colour (likely-early similar), or the likely-late distractor colour (likely-late similar). Example targets in each category are illustrated in Figure 4.4A. 'Neutral' coloured targets (Supplementary Figure 7.15) were not analysed here.

I hypothesised that colour type would interact significantly with onset time. If participants' handling of each distractor colour was tuned to the regularities, then hits would be lowest and RTs slowest for *early* onset targets similar to the *likely-early* distractor colour, and for *late* onset targets similar to the *likely-late* distractor colour. I also hypothesised that these effects may strengthen across the learning session, leading to interactions with *block number*.

4.3.6 Statistical Analysis

All analyses used R (R Core Team, 2024), and plots were created using the *ggplot2* package (Wickham, 2016). I used a two-tailed 5% error criterion to test for significance. Full datasets, and all data cleaning and analysis scripts, are available on OSF https://osf.io/jbd86/files.

Data Cleaning. Data cleaning procedures were similar to those in previous chapters. First, data were excluded from any participant who did not complete all experimental blocks or who

reported in a debrief that their data should not be analysed. These steps excluded three participants. Data from the learning and testing sessions were then cleaned separately using an identical procedure. If a participant's data from either session were excluded, then all their data were excluded. Additional participants were tested to replace excluded datasets until the pre-determined sample size of 80 was reached. In total, 110 datasets were collected, with 30 excluded.

Data were initially excluded based on low accuracy, assumed to indicate either disengagement or poor task understanding. Accuracy was first assessed using *d'*, calculated as described in Variables of Interest. Data from any participant with *d'* <= 0 were excluded, as this indicated that sensitivity for collecting targets over distractors was at or below chance level. This excluded one participant. I had also planned to exclude data from any participant whose *d'* was more than 3*SD* below the mean *d'* across participants, but no participant met this criterion.

Next, data were excluded from any participant whose hit rate varied substantially across target colours. Ideally, participants would show similar accuracy across colours. However, trends in the behavioural data and debrief responses indicated that numerous participants had difficulty distinguishing between some of the targets and distractors. This was problematic because confusing temporally unpredictable targets for distractors would impede participants' abilities to learn the distractor-based feature-temporal regularities. To identify cases of confusion between targets and distractors, I calculated the hit rate for each of the six target colours for each participant. The highest hit rate for any colour was taken as an indication of a participant's maximum capability. If a participant's hit rate for any other colour fell below half of this maximum, their data were excluded, as this suggested that they may have avoided targets of this colour due to confusing them with distractors. This step excluded 22 participants.

Following accuracy-based exclusions, RT data for stimulus responses were used to remove premature or outlier taps. Firstly, all responses with RT < 200 ms were removed. Then, within each

participant and session, remaining RTs more than 3*SD* from that participant's median RT were removed. This was done separately for targets and distractors, as their RT distributions were distinct. For the final participant sample, these steps removed 3.27% of responses from the learning session and 4.02% from the testing session. I had planned to exclude data from any participant for whom more than one-third of responses were removed, but no participant met this criterion. Finally, data were excluded from participants whose median RT was more than 3*SD* from the median RT across all participants, excluding four datasets.

Basic Effects of Distraction on Performance Over Time. *Target Hits and RTs.* I analysed the effects of *distraction timing* (none, early, or late), *target onset window* (early or late), *block number* (1-4), and their interactions on hit rates and RTs in the learning session using two separate 3 x 2 x 4 repeated-measures ANOVAs. Here, and for all subsequent ANOVAs in this chapter, I employed the *ezANOVA* function from the *ez* package (M. A. Lawrence, 2016). Aggregated hit rates and RT scores were transformed prior to analysis, if required, to meet the assumption of normality. Here, and in all subsequent analyses, transformations followed recommendations of the boxcox function of the MASS package (Venables & Ripley, 2002).

Significant main effects of distractor timing were followed with two repeated-measures *t*-tests that compared scores from trials with early and late distraction, separately, to distraction-absent trials. A significant main effect of block was followed by a *t*-test comparing scores between the first and final learning blocks. All follow-up *t*-tests were supplemented by Cohen's *d* values (calculated using untransformed data) and Bayesian *t*-tests using transformed data employing the *BayesFactor* package (Morey & Rouder, 2022). Interpretations of Bayes factor values are given in Table 2.2.

I hypothesised that distractor timing would interact with target onset window and block number. Any such significant interaction was first followed with two pre-planned ANOVAs analysing

the effect of distractor timing separately for early and late onset targets, or for the first and final learning blocks. If a significant effect of distractor timing was found for either onset window, or block, this was followed with two pre-planned *t*-tests comparing performance in early and late distraction trials, separately, to performance in distraction-absent trials for the relevant onset window or block.

For consistency with other chapters, a supplementary analysis assessed the effects of distraction on performance in terms of IES. The results of this analysis are provided in Supplementary Figure 7.14 and Supplementary Table 7.18.

d'. I analysed the effects of *stimulus onset window* (early vs. late), learning *block number* (1-4), and their interaction on *d'* using a 2 x 4 repeated-measures ANOVA. A significant main effect of block was followed with a pre-planned *t*-test comparing *d'* between the first and final learning blocks.

Testing Session: Analysing Performance Under Feature-Temporally Likely Versus Unlikely Distraction. I analysed the effects of *onset window* (early vs. late), *distractor likelihood* (likely-early vs. likely-late), and their interaction on both *d'* and target RTs using two separate 2 x 2 repeated-measures ANOVAs.

Learning Session: Analysing Effects of Colour Similarity to Feature-Temporally Likely Versus Unlikely Distraction on Target Performance. I analysed the effects of *target onset window* (early vs. late), *colour type* (likely-early similar vs. likely-late similar), learning *block number* (1-4), and their interactions on both target hit rate and RTs using two separate 2 x 2 x 4 repeated-measures ANOVAs. Where a significant interaction between onset window and colour type was found, it was followed by two pre-planned *t*-tests, each comparing performance between the levels of colour type, separately for early and late onset targets.

A further supplementary analysis assessed the effects of target colour on performance in terms of IES. The results of this analysis are provided in Supplementary Figure 7.16 and Supplementary Table 7.21.

4.4 Results

4.4.1 Basic Effects of Distraction on Performance Over Time

For visualisation purposes, Figure 4.2 shows participants' average hit rate (A) and RT (B) for identifying targets across onset times in trials with no distraction, early distraction, and late distraction in the learning session. These plots show that targets appearing alongside either early or late distractors were, numerically, hit less often and more slowly compared to baseline levels in distractor-absent trials. Numerically, distractors caused a time-varying decline in task performance for both hits and RTs. These effects are analysed below with onset times grouped into two categories: early and late (see Variables of Interest).

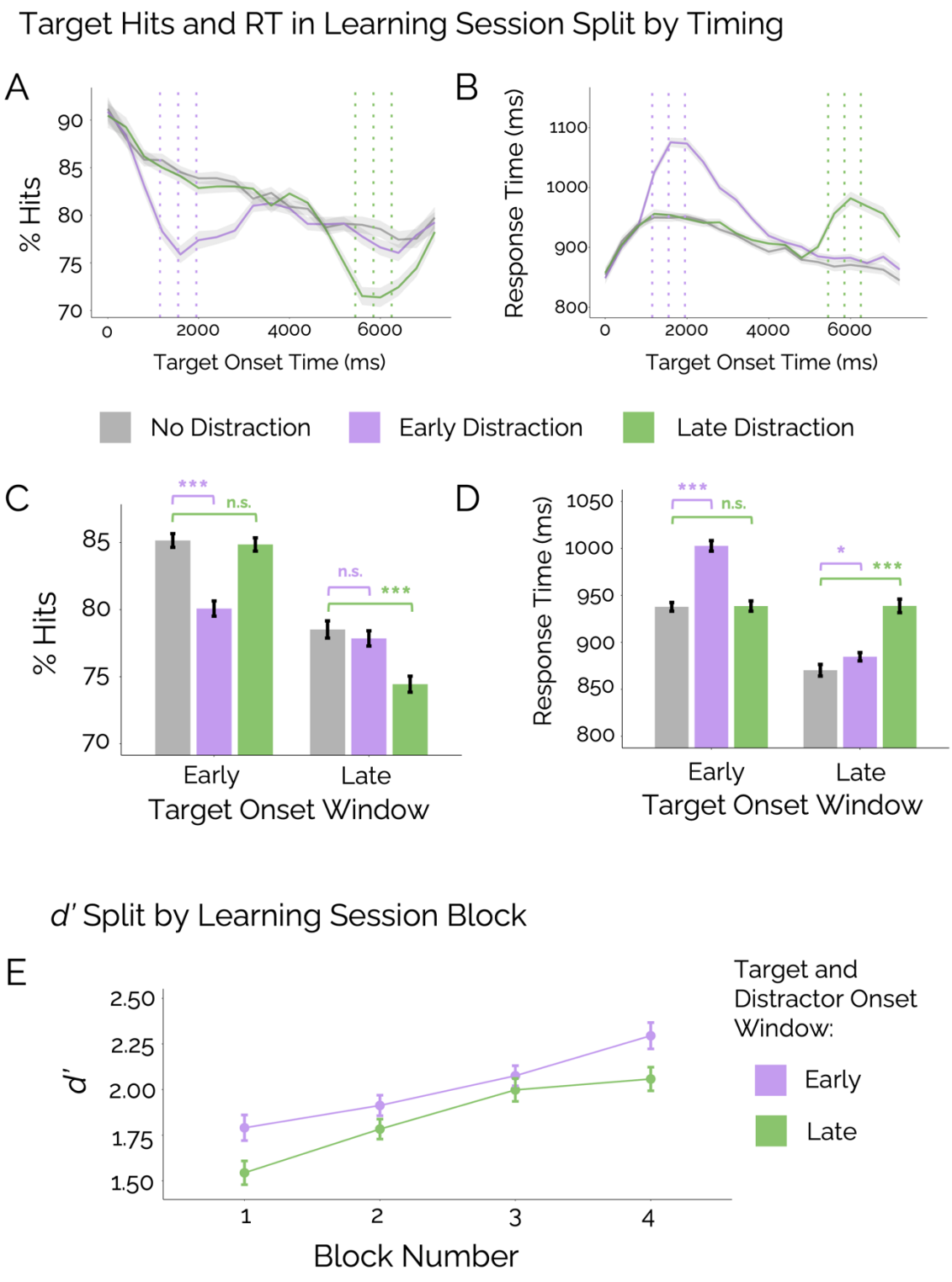


Figure 4.2. (A & B) Percentage of targets hit (A) and response times for hits (B), across target onset times, for learning session trials with no distraction (grey), early distraction (purple), and late distraction (green). The solid grey, purple, and green lines represent mean values, while the grey shaded areas represent ±1 *SE* around the mean. For these visualisations, data were smoothed by

rounding target onset times to the nearest 400 ms. The vertical dotted lines indicate the onset times for the three distractors in the early distraction wave (purple) and the three distractors in the late wave (green). **(C & D)** Mean (untransformed) percentage hits (C) and RTs (D) for learning session targets with an 'early' or 'late' onset time (see Variables of Interest) in trials with no distraction (grey bar), early distraction (purple bar), or late distraction (green bar). Here, and in subsequent plots, error bars represent ±1 standard error (*SE*) around the mean. The statistical significance of comparisons between trials where distraction appeared early, or late, to trials with no distraction is indicated with asterisks: *** = $p < .001$, * = $p < .05$, n.s. = not significant. **(E)** Mean *d'* scores for performance identifying targets and avoiding distractors with early and late onset times, in each learning block.

Target Hits & RTs. The hits and RT analyses found that distractors significantly impaired performance identifying targets. In line with *boxcox* recommendations, hits underwent a squared transformation prior to analysis, while RTs underwent a square root transformation. Full ANOVA outputs for hits and RT analyses are given in Table 4.1 and Table 4.2, respectively.

Table 4.1

Effects of Distraction on Target Hits in Learning Session Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	**86.39**	**1**	**79**	**< .001**	**.039**	**NA**
Distractor Timing	**29.28**	**2**	**158**	**< .001**	**.007**	**NA**
Block Number	**21.73**	**2.08[1]**	**164.69[1]**	**< .001[1]**	**.022**	**0.69**
Target Onset Window : Distractor Timing	**66.06**	**1.63[1]**	**128.46[1]**	**< .001[1]**	**.013**	**0.81**
Target Onset Window : Block Number	1.62	3	237	.185	< .001	NA
Distractor Timing : Block Number	**2.62**	**5.15[1]**	**406.65[1]**	**.029[1]**	**.001**	**0.86**
Target Onset Window : Distractor Timing : Block Number	1.11	6	474	.356	< .001	NA

Note. Significant predictors are shown in bold. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

Table 4.2

Effects of Distraction on Target RTs in Learning Session Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	**64.63**	**1**	**79**	**< .001**	**.044**	**NA**
Distractor Timing	**47.89**	**2**	**158**	**< .001**	**.013**	**NA**
Block Number	**49.67**	**2.46[1]**	**194.31[1]**	**< .001[1]**	**.039**	**0.82**
Target Onset Window : Distractor Timing	**119.58**	**1.63[1]**	**129.10[1]**	**< .001[1]**	**.024**	**0.82**
Target Onset Window : Block Number	**3.17**	**3**	**237**	**.025**	**< .001**	**NA**
Distractor Timing : Block Number	**2.31**	**6**	**474**	**.033**	**.001**	**NA**
Target Onset Window : Distractor Timing : Block Number	0.82	5.02[1]	396.64[1]	.533[1]	< .001	0.84

[1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

The hits ANOVA revealed a significant main effect of target onset window ($p < .001$). Overall, participants hit more targets that appeared early during trials (M = 83.37%, SD = 5.04%), than

appeared late (*M* = 76.95%, *SD* = 5.04%). Though hit less often, late targets were hit significantly more quickly (*M* = 898 ms, *SD* = 49 ms) than early targets (*M* = 959 ms, *SD* = 49 ms; *p* < .001).

Both hits and RT analyses also revealed a significant main effect of block number (*p* < .001, Greenhouse-Geisser correction) reflecting performance improvements across learning. Follow-up *t*-tests revealed that targets were hit significantly more often in the final learning block (*M* = 82.30%, *SD* = 6.96%) than the first (*M* = 76.64%, *SD* = 6.96%; *t*(79) = -5.26, *p* < .001, *d* = 0.58, BF_{10} > 1000). Targets in the final learning block (*M* = 902 ms, *SD* = 54 ms) were also identified significantly more quickly than those in the first (*M* = 982 ms, *SD* = 54 ms; *t*(79) = 9.51, *p* < .001, *d* = 1.05, BF_{10} > 1000).

For RT only, onset window and block number interacted significantly (*p* = .025), with the difference in response speed between onset windows increasing across the learning session. However, late targets in both the first (M = 952 ms, SD = 58 ms) and the last (M = 860 ms, SD = 50 ms) learning block were identified significantly faster than early targets in the first (M = 1005 ms, SD = 58 ms; t(79) = 5.77, p < .001, d = 0.65, BF_{10} > 1000) and last (M = 934 ms, SD = 50 ms; t(79) = 9.44, p < .001, d = 1.04, BF_{10} > 1000) learning block, respectively.

The main effect of distractor timing was significant for both hits (*p* < .001) and RT (*p* < .001). For hits, follow-up *t*-tests revealed that significantly fewer targets were hit overall during trials where distraction appeared either early (*M* = 79.02%, *SD* = 2.49%; *t*(79) = -6.79, *p* < .001, *d* = -0.75, BF_{10} > 1000), or late (*M* = 79.75%, *SD* = 2.51%; *t*(79) = -5.29, *p* < .001, *d* = -0.56, BF_{10} > 1000), compared to distractor-absent trials (*M* = 81.91%, *SD* = 2.83%). Similarly, for RT, targets were identified significantly more slowly in trials where distraction appeared either early (*M* = 947 ms, *SD* = 27 ms; *t*(79) = 8.55, *p* < .001, *d* = 0.94, BF_{10} > 1000) or late (*M* = 941 ms, *SD* = 24 ms; *t*(79) = 8.07, *p* < .001, *d* = 0.88, BF_{10} > 1000), compared to never (*M* = 908 ms, *SD* = 29 ms).

For both hits and RT, distractor timing interacted significantly with target onset window (p < .001, Greenhouse-Geisser correction) and, separately, with block number (hits: p = .029, Greenhouse-Geisser correction; RT: p = .033). These interactions are broken down below.

Distractor Timing x Target Onset Window. For *early* targets, distractor timing significantly affected hits (F(2,158) = 84.77, p < .001, η^2_G = .036, Greenhouse-Geisser correction; Figure 4.2C) and RTs (F(2,158) = 124.75, p < .001, η^2_G = .050, Greenhouse-Geisser correction; Figure 4.2D). In *early distraction* trials, early target hits (M = 80.08%, SD = 3.56%) were significantly lower than in distraction-absent trials (M = 85.15%, SD = 2.48%; t(79) = -10.24, p < .001, d = -1.12, BF_{10} > 1000), and early target RTs (M = 1003 ms, SD = 35 ms) were significantly slower than in distraction-absent trials (M = 938 ms, SD = 27 ms; t(79) = 12.89, p < .001, d = 1.41, BF_{10} > 1000). In *late distraction* trials, neither early target hits (M = 84.86%, SD = 2.59%; (t(79) = -0.82, p = .415, d = -0.10, BF_{10} = 0.17), nor early target RTs (M = 939 ms, SD = 28 ms; t(79) = 0.18, p = .857, d = 0.02, BF_{10} = 0.13) differed significantly from in distraction-absent trials. This latter finding was expected, as late distraction trials and distraction-absent trials were identical during the early time window.

For *late* targets, distractor timing also significantly affected hits (F(2,158) = 24.38, p < .001, η^2_G = .015; Figure 4.2C) and RTs (F(2,158) = 57.94, p < .001, η^2_G = .038; Figure 4.2D). In *early distraction* trials, late target hits (M = 77.86%, SD = 3.67%) did not differ significantly from those in distraction-absent trials (M = 78.52%, SD = 4.06%; t(79) = -1.48, p = .143, d = -0.13). However, evidence for this null effect was only anecdotal (BF_{10} = 0.35). In contrast, late target *RTs* in early distraction trials (M = 885 ms, SD = 39 ms) were significantly slower than in distraction-absent trials (M = 870 ms, SD = 41 ms; t(79) = 2.49, p = .015, d = 0.27), though evidence for this difference was again only anecdotal (BF_{10} = 2.21). In *late distraction* trials, late target hits (M = 74.44%, SD = 4.69%) were significantly lower than in distraction-absent trials (t(79) = -6.08, p < .001, d = -0.63, BF_{10} > 1000), and late target RTs (M = 938 ms, SD = 47 ms) were significantly slower (t(79) = 9.51, p < .001, d = 1.06, BF_{10} > 1000).

As hypothesised, performance was impaired when targets appeared at the same time as distractors, in comparison to distraction-absent trials. This was true in terms of hits and RTs, and for both early and late distraction. These results confirm that the distractors distracted participants, and that this could be measured via impairments in collecting targets. Interestingly, I also found evidence that some effects of early distraction persisted into the late time window. The persistence of these effects differed between measures: hit deficits had mostly recovered by the time late targets appeared in the same trial, while RT deficits remained. However, evidence for both findings was only anecdotal, suggesting these differences may be slight.

Distractor Timing x Block Number. In the *first learning block*, distractor timing significantly affected both hits ($F(2,158) = 10.23$, $p < .001$, $\eta^2_G = .007$) and RTs ($F(2,158) = 6.46$, $p = .002$, $\eta^2_G = .006$), visualised in Supplementary Figure 7.13A. Hits were significantly lower during trials where distractors appeared either early ($M = 75.37\%$, $SD = 4.33\%$; $t(79) = -4.40$, $p < .001$, $d = -0.49$, $BF_{10} = 554.71$), or late ($M = 76.16\%$, $SD = 4.65\%$; $t(79) = -3.06$, $p = .003$, $d = -0.34$, $BF_{10} = 8.85$), relative to never ($M = 78.37\%$, $SD = 4.48\%$). RTs were significantly slower during trials where distractors appeared early ($M = 993$ ms, $SD = 54$ ms; $t(79) = 3.41$, $p = .001$, $d = 0.36$, $BF_{10} = 23.70$), or late ($M = 986$ ms, $SD = 50$ ms; $t(79) = 2.64$, $p = .010$, $d = 0.28$, $BF_{10} = 3.15$), compared to never ($M = 966$ ms, $SD = 52$ ms).

By the *final learning block*, distractor timing still significantly affected both hits ($F(2,158) = 4.16$, $p = .017$, $\eta^2_G = .004$) and RTs ($F(2,158) = 24.96$, $p < .001$, $\eta^2_G = .026$), visualised in Supplementary Figure 7.13B. In *early distraction* trials, in contrast to the first block, hits ($M = 82.41\%$, $SD = 5.26\%$) did not differ significantly from those in distraction-absent trials ($M = 83.33\%$, $SD = 4.61\%$; $t(79) = -1.38$, $p = .173$, $d = -0.13$, $BF_{10} = 0.30$). RTs in early distraction trials ($M = 918$ ms, $SD = 54$ ms) were, however, still significantly slower than in distraction-absent trials ($M = 869$ ms, $SD = 49$ ms; $t(79) = 5.80$, $p < .001$, $d = 0.65$, $BF_{10} > 1000$). In *late distraction* trials, as for the first learning block, performance was

significantly impaired relative to distraction-absent trials in both hits (M = 81.12%, SD = 5.12%; $t(79)$ = -3.13, p = .002, d = -0.33, BF_{10} = 10.87) and RTs (M = 916 ms, SD = 46 ms; $t(79)$ = 6.49, p < .001, d = 0.73, BF_{10} > 1000).

The hits results suggest that participants improved at handling early, but not late distraction across the learning session. As the likely timing of each distractor colour was counterbalanced across participants, these findings are unlikely due to differences in the ability to suppress low-level stimulus features. In contrast, RT costs for both early and late distraction persisted in the final learning block. In fact, the sizes of distraction effects on RTs were larger in the final learning block than in the first. This suggests that, although participants may have learnt to suppress early distraction to collect more early targets, this came at the cost of slower RTs. This is likely due in part to motor limitations when collecting multiple successive targets.

d'. The hits and RT analyses revealed significant main effects of block number that indicated that participants' overall ability to collect targets improved over the course of learning. However, these measures provide inconsistent evidence as to whether participants improved at handling distraction specifically. The *d'* analysis, which accounted for both target hits and distractor false alarms, showed that participants did in fact improve their sensitivity for collecting targets over distractors across the learning session.

In line with *boxcox* recommendations, *d'* scores were not transformed prior to analysis. The ANOVA (see Table 4.3) revealed a significant main effect of onset window (p = .001; Figure 4.2E). Overall, *d'* was higher when targets and distractors appeared early during trials (M = 2.02, SD = 0.40), compared to late (M = 1.85, SD = 0.40). The main effect of block number was also significant (p < .001, Greenhouse-Geisser correction; Figure 4.2E). A follow-up t-test revealed that performance improved across learning, with significantly higher *d'* scores in the final learning block (M = 2.18, SD

= 0.49) than the first (M = 1.67, SD = 0.49; $t(79) = 6.53$, $p < .001$, $d = 0.73$, $BF_{10} > 1000$). The interaction between onset window and block number was not significant ($p = .240$).

Table 4.3

d' in Learning Session Full ANOVA Output

Predictor	F	df_1	df_2	p	η^2_G	ε
Onset Window	**7.61**	**1**	**79**	**.001**	**.008**	**NA**
Block Number	**23.48**	**2.55[1]**	**201.63[1]**	**< .001[1]**	**.040**	**0.85**
Onset Window : Block Number	1.41	3	237	.240	.001	NA

[1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

During learning, *d'* was consistently higher for stimuli that appeared early in trials compared to late (Figure 4.2E), suggesting that participants were better able to collect targets over distractors earlier in the trial. As hypothesised, *d'* scores increased across the learning session, indicating improved ability to collect targets over distractors, regardless of timing (early or late). The next section of the results examines whether any learnt handling of distractor colours was temporally tuned in accordance with the task's feature-temporal regularities.

4.4.2 Testing Session: Performance For Feature-Temporally Likely Versus Unlikely Distraction

d'. The *d'* analysis provided no evidence that participants were better able to handle temporally likely distractors compared to temporally unlikely ones. In line with *boxcox*

recommendations, *d'* scores were not transformed for analysis. The ANOVA (see Table 4.4) revealed a significant main effect of onset window (p = .001). Consistent with the learning session, *d'* scores were higher when targets and distractors appeared early during trials (M = 2.34, SD = 0.31) compared to late (M = 2.02, SD = 0.31). The main effect of distractor likelihood was not significant (p = .139), indicating that participants' ability to prioritise targets over distractors did not depend on whether distractors were in the likely-early or likely-late colour. This null result was expected, as the assignments of each hue as likely-early or likely-late were counterbalanced across participants.

In contrast with my hypothesis, the interaction between onset window and distractor likelihood was not significant (p = .455; Figure 4.3A). This suggests that participants' ability to collect targets while avoiding distractors of either colour did *not* vary based on which colour was temporally likely.

Table 4.4

Testing Session *d'* Full ANOVA Output

Predictor	F	df_1	df_2	p	η^2_G
Onset Window	**41.70**	**1**	**79**	**< .001**	**.026**
Distractor Likelihood	2.24	1	79	.139	.002
Onset Window : Distractor Likelihood	0.56	1	79	.455	< .001

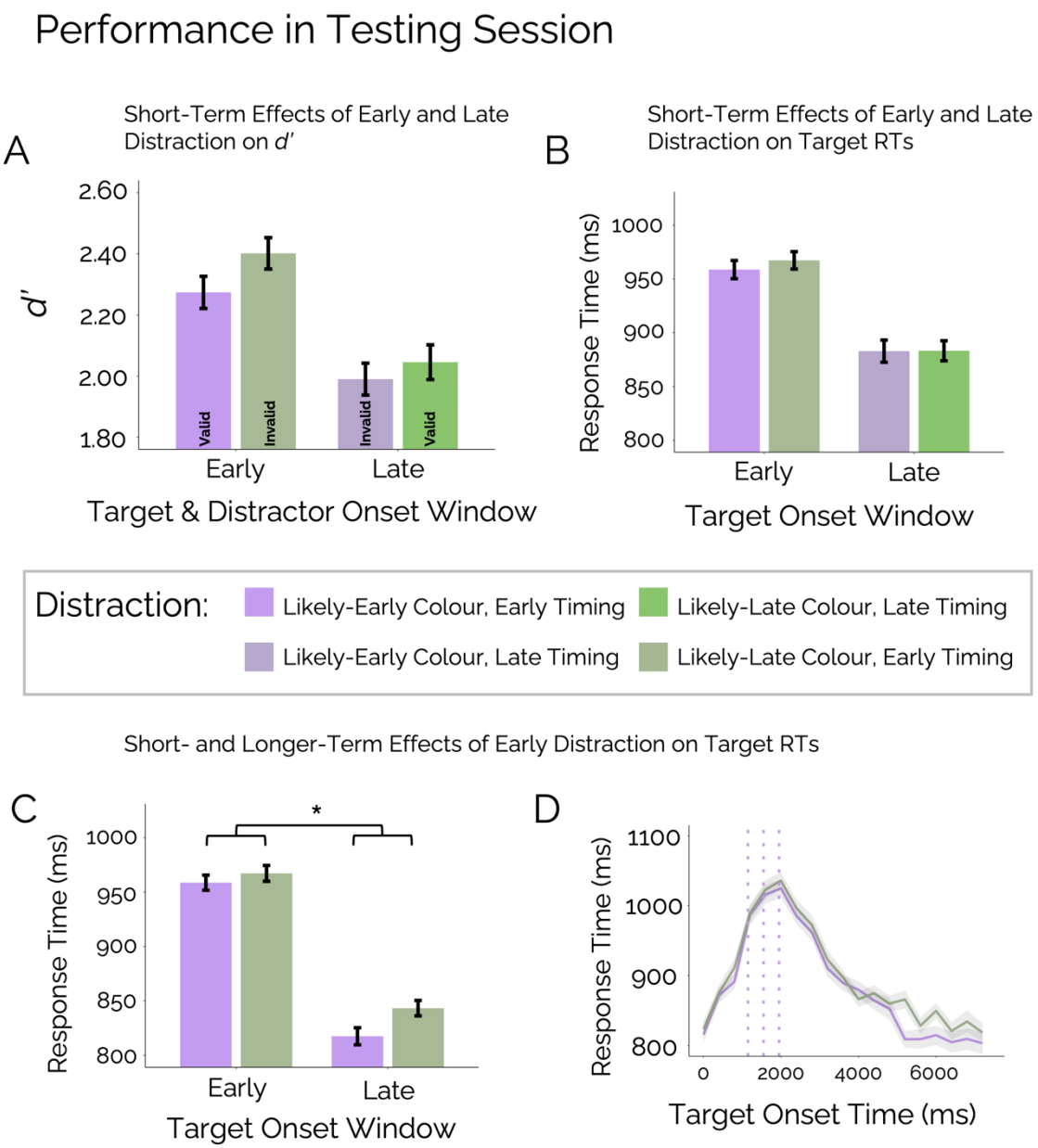


Figure 4.3. (A) Mean *d'* scores for performance identifying targets and avoiding distractors in the testing session for targets and distractions that onset early or late, and for distractors that appeared in the likely-early or likely-late colour. **(B)** Mean RTs for targets that appeared concurrently with distraction in the testing session, for targets with an early or late onset time, appearing amongst distractors in the likely-early or likely-late colour. **(C)** Mean (untransformed) testing session RTs for targets appearing, early or late, in trials with early distractors in the likely-early or likely-late colour. Here, a statistically significant main effect of distractor likelihood (likely-early vs. likely-late) is indicated with * = $p < .05$. **(D)** Mean RTs for target hits across target onset times in trials with temporally likely and unlikely early distraction. Data were smoothed here by rounding onset times to the nearest 400 ms. The onset times for the early distractors are indicated by the vertical dotted lines.

RTs. ***Short-Term Effects of Temporally Likely and Unlikely Early and Late Distraction.*** The previous learning session analysis revealed short-term effects of distraction on target RTs: participants responded significantly more slowly if targets appeared alongside distractors. The current analysis tested whether RTs for targets appearing at the same time as distractors were further modulated by the temporal likelihood of the distractor colour. However, no such effect was observed.

RTs were not transformed prior to analysis. The ANOVA (see Table 4.5) revealed a significant main effect of onset window ($p < .001$). As in the learning session, RTs were faster for late targets (M = 885 ms, SD = 72 ms) than early targets (M = 963 ms, SD = 72 ms). The main effect of distractor likelihood was not significant ($p = .563$), indicating that RTs were not affected by whether distractors were in the likely-early or likely-late colour.

Similar to the *d'* analysis, the interaction of interest between onset window and distractor likelihood was not significant ($p = .576$; Figure 4.3B). Contrary to my hypothesis, the speed with which participants collected targets in the presence of distraction did *not* depend on whether the distractors' colour was temporally likely.

Table 4.5

Testing Session RT Full ANOVA Output: Targets Concurrent With Early and Late Distraction

Predictor	F	df_1	df_2	p	η^2_G
Target Onset Window	**47.21**	**1**	**79**	**< .001**	**.062**
Distractor Likelihood	0.34	1	79	.563	<.002
Target Onset Window : Distractor Likelihood	0.32	1	79	.576	< .001

Short- and Longer-Term Effects of Temporally Likely and Unlikely Early Distraction. The previous analysis only considered targets that appeared concurrently with distractors. However, the above learning session analysis revealed that early distractors affected RT performance for *late*, as well as early onset targets. Thus, to explore both short- and longer-term effects, here I investigated how the temporal likelihood of early distractors influenced RTs throughout the trial.

I used a 2 x 2 repeated-measures (*target onset time* x *early distractor likelihood*) ANOVA to analyse RTs for early versus late targets in trials with early distraction in the temporally likely versus unlikely colour. RTs underwent a square root transformation prior to analysis. The ANOVA (see Table 4.6) again revealed a significant main effect of onset window ($p < .001$), with faster RTs for late targets (M = 832 ms, SD = 63 ms) than early targets (M = 963 ms, SD = 63 ms).

In contrast to the previous RT analysis, the main effect of *early* distractor likelihood was significant ($p = .011$; Figure 4.3C). Overall, participants responded significantly more slowly during trials where early distraction appeared in the invalid likely-late colour, compared to the valid likely-early colour, demonstrating a performance cost for the temporally unlikely distractor colour that persisted into the late time window. These extended effects of early distractor likelihood are illustrated in a more continuous manner for target onset times throughout the trial in Figure 4.3D. The interaction between onset window and early distractor likelihood was not significant ($p = .095$; Figure 4.3C), suggesting that the benefit for temporally likely early distraction was not significantly greater for early or late targets.

Table 4.6

Testing Session RT Full ANOVA Output: Early and Late Targets With Early Distraction

Predictor	*F*	df_1	df_2	*p*	η^2_G
Target Onset Window	**170.57**	**1**	**79**	**< .001**	**.017**
Early Distractor Likelihood	**6.78**	**1**	**79**	**.011**	**.004**
Target Onset Window : Early Distractor Likelihood	2.86	1	79	.095	.001

Overall, the testing session analyses found that, when targets overlapped temporally with distractors, neither participants' sensitivity to collect targets over distractors (*d'*), nor their speed collecting targets (RT), was significantly affected by whether distractors appeared in the temporally likely or unlikely colour. This suggests that participants either did not form feature-temporal predictions about distractors, or that these predictions did not modulate distractor handling in a way that measurably affected short-term performance. However, when targets appearing both alongside *and after* early distraction were considered, RTs were significantly slower in trials where early distraction appeared in the temporally unlikely versus temporally likely colour. This pattern suggests that performance costs associated with feature-temporally unexpected distraction may have emerged more gradually, potentially reflecting delayed cognitive consequences such as surprise or effort in updating internal predictions. The findings are consistent with participants having predicted that early distractors would appear in the likely-early colour, even if a violation of this prediction did

not impair immediate performance, perhaps due to high task proficiency or effective inhibitory control.

4.4.3 Learning Session: Effects of Colour Similarity to Feature-Temporally Likely Versus Unlikely Distraction on Target Performance

Hits. This hits analysis provided evidence that how frequently participants collected targets similar in colour to the likely-early or likely-late distractors varied significantly across time in the trial. The ANOVA (see Table 4.7) revealed no significant main effect of colour type (p = .066), indicating that, overall, hit rates did not differ between targets similar in colour to the likely-early and likely-late distractors.

However, as hypothesised, the interaction between colour type and onset window was significant (p = .027). When targets appeared early, those in a similar colour to the likely-early distractors were hit significantly less (M = 82.64%, SD = 4.88%) than those in a similar colour to the likely-late distractors (M = 84.88%, SD = 4.88%; $t(79) = -2.53$, p = .014, d = -0.28; Figure 4.4B), though evidence for this difference was only anecdotal (BF_{10} = 2.40). In contrast, when targets appeared late, there was no significant difference in hits between targets in similar to the likely-early (M = 76.93%, SD = 5.17%) and likely-late distractors (M = 77.48%, SD = 0.52%; $t(79) = -0.67$, p = .505, d = -0.07, BF_{10} = 0.15; Figure 4.4B).

Neither the two-way interaction between colour type and block number (p = .246), nor the three-way interaction between colour type, onset time, and block number (p = .182) was significant.

Table 4.7

Learning Session: Effects Of Colour Type on Target Hits Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	**59.01**	**1**	**79**	**< .001**	**.031**	**NA**
Colour Type	3.47	1	79	.066	.002	NA
Block Number	**20.00**	**2.37[1]**	**187.11[1]**	**< .001[1]**	**.028**	**0.79**
Target Onset Window : Colour Type	**5.09**	**1**	**79**	**.027**	**< .001**	**NA**
Target Onset Window : Block Number	0.20	3	237	.896	< .001	NA
Colour Type : Block Number	1.39	3	237	.246	<.001	NA
Target Onset Window : Colour Type : Block Number	1.63	3	237	.182	< .001	NA

Note. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

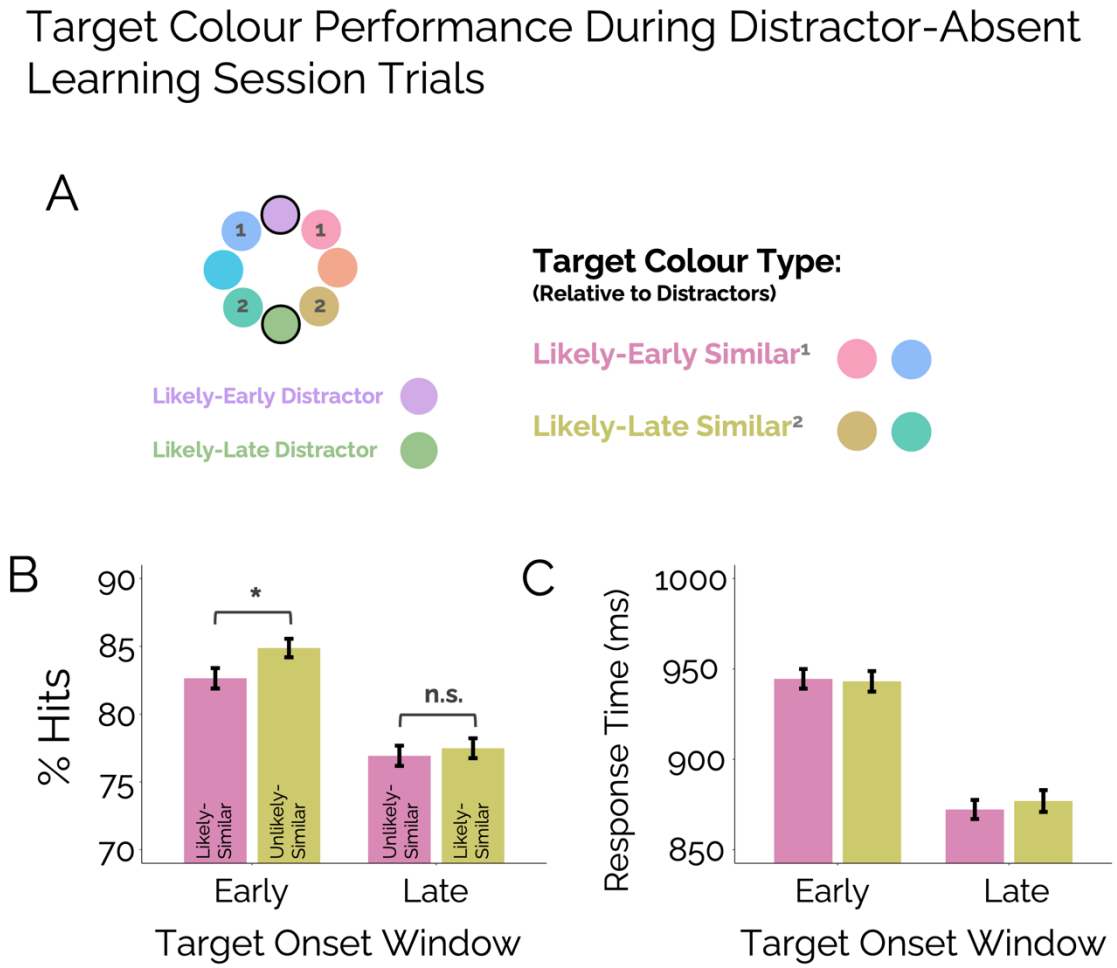


Figure 4.4. (A) Example targets for levels of the '*colour type*' variable. Targets appearing in a similar (neighbouring) colour to the likely-early or likely-late distractors, for the example likely-early and likely-late distractors in Figure 4.1D. **(B)** Mean hits for targets in distractor-absent learning session trials that appeared early or late in the trial, and in a colour similar to the likely-early or likely-late distractors. The significance of follow-up comparisons between levels of colour type for each onset window are indicated with * = $p < .05$ and n.s. = not significant. **(C)** Mean RT for targets in distractor-absent learning session trials that appeared early or late in the trial, and in a colour similar to the likely-early or likely-late distractors

RTs. Unlike for hits, the RT analysis found no difference in how participants responded to targets similar to the temporally likely versus unlikely distractors. The ANOVA (see Table 4.8) revealed that the main effect of colour type was not significant ($p = .802$). Participants identified targets in similar colours to the likely-early and likely-late distractors at a similar speed overall. Further, and in

contrast to my hypothesis, the interaction between colour type and onset window was not significant (p = .201; Figure 4.4C), nor were interactions between colour type and block number (p = .246), and between colour type, onset time, and block number (p = .182).

Table 4.8

Learning Session: Effects Of Colour Type on Target RTs Full ANOVA Output

Predictor	F	df_1	df_2	p	η^2_G	ε
Target Onset Window	**65.32**	**1**	**79**	**< .001**	**.049**	**NA**
Colour Type	0.06	1	79	.802	< .001	NA
Block Number	**36.92**	**2.71[1]**	**213.93[1]**	**< .001[1]**	**.043**	**0.90**
Target Onset Window : Colour Type	1.67	1	79	.201	< .001	NA
Target Onset Window : Block Number	1.29	2.65[1]	209.20[1]	.278[1]	.001	0.88
Colour Type : Block Number	0.21	2.44[1]	192.85[1]	.855[1]	< .001	0.81
Target Onset Window : Colour Type : Block Number	0.32	3	237	.814	< .001	NA

Note. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

Together, these analyses suggest that, while the *speed* at which participants collected targets of each colour type did not vary with target timing, participants *hit* fewer targets similar to the temporally likely distractor colour at early times during trials. This pattern is consistent with participants using the feature-temporal regularities associated with early distractors to dynamically guide their behaviour during trials, selectively avoiding targets similar to the likely-early distractors when these distractors were predicted to occur.

4.5 Discussion

In this study I investigated the effects of feature-temporal distractor regularities on performance in a DVS task. Specifically, participants completed a tablet-based online task in which target responses served as a proxy measure for attentional engagement across time. The present investigation furthers the limited previous work on temporally tuned suppression of distractor properties within other domains. Where Xu et al. (2021) investigated the effects of distractor-based spatiotemporal regularities on performance, I investigated feature-temporal regularities. Although the hypothesis that participants would perform better during feature-temporally likely versus unlikely distraction was not supported, the findings did suggest that participants acquired predictions based on the task's feature-temporal regularities. This learning influenced behaviour in other ways, specifically, in terms of the lasting effects of distraction on performance, and by temporally-tuning performance for targets in similar colours to distractors.

The study was successful in its prerequisite aim of finding deficits in target performance to evidence participant distraction. This validation was essential, as not all intended distractors have the capability to distract (Wöstmann et al., 2022), and since the study investigated distraction in a new, dynamic task rather than in a well-established static paradigm, such as the additional-singleton task. The finding of performance impairments during distraction waves indicated that participants

engaged with the distractors during learning, increasing the likelihood that participants also encoded their feature-temporal regularities.

It is worth noting that, because the number of targets was held constant across all trials, the total number of visible stimuli was higher on average during periods *with* distraction than without. Increased visual crowding alone can impair perceptual discrimination (Whitney & Levi, 2011). However, maintaining a consistent number of targets ensured fair comparisons across trial types, as motor limitations when collecting multiple successive targets were equivalent. Thus, performance in distractor-absent trials served as a baseline for participants' maximum capabilities if they had not engaged with distractors at all.

The dynamic nature of the task yielded insight into how the basic effects of distraction on performance varied depending on when targets and distractors appeared within a trial. Firstly, during distractor-present trials, participants showed greater sensitivity for collecting targets over distractors (*d'*) when stimuli appeared early, compared to late. This may reflect stronger attentional control or response inhibition at the beginning of trials, whereas fatigue or cognitive overload due to the cumulative demands of sustained target collection may have hindered performance at later times during the trials.

Secondly, when distractors appeared early, distraction effects persisted throughout the trial: responses were slower not only for early targets that appeared concurrently with the distractors but also, though to a lesser extent, for late targets that appeared *after* the distractors. Recent multi-target dynamic visual search studies (e.g., Boettcher et al., 2022; Grössle et al., 2023; Shalev et al., 2024; Tünnermann et al., 2021), including those in Chapters 2 and 3, have kept the level of distraction consistent throughout trials. However, the present findings highlight the utility of such tasks for investigating how more transient distraction can affect performance differently at different times.

I also investigated whether participants improved at handling distraction over the course of learning. This was relevant because improvements could be consistent with participants having established learnt feature-based distractor handling, which may have been tuned to the task regularities. Some results suggested that participants did *not* disengage from distractors by the end of learning: in the final learning block, both early and late distractors still significantly slowed target RTs, and late distraction continued to impair target hits. However, other results did reflect improvements. Early distractors no longer impaired target hits by the final learning block, and *d'* scores for both early and late stimuli steadily increased across blocks, suggesting participants more sensitively selected targets over distractors with task experience. D-prime is a particularly informative measure here, as it captures improvements in both target collection and distractor avoidance, accounting for differences in response biases between participants (Stanislaw & Todorov, 1999). The observed improvement in sensitivity across blocks aligns with theories of learnt distractor suppression (see Gaspelin & Luck, 2019). Such theories suggest that suppression of distractor features or locations arises from repeated exposure to these elements, rather than from initial, willed avoidance, reflecting findings from, e.g., Cunningham & Egeth (2016), Noonan et al. (2016) and Stilwell & Vecera (2019). While participants were explicitly told which colours to avoid, any suppression may have emerged only after repeated in-task distractor experience.

Moving on, the primary aim of the present study was to investigate whether participants formed feature-temporal predictions about distractors and used them adaptively to adjust their behaviour throughout trials. Similarly to previous chapters, which focused on temporal predictions about *target* colours, this was first assessed by comparing testing session performance for temporally likely versus unlikely *distractor* colours. This comparison initially focused only on performance for targets that appeared concurrently with distractors, as, intuitively, this should be most affected by distraction (see Basic Effects of Distraction on Performance Over Time). However, contrary to

expectations, here the effect of distractor likelihood (likely-early or likely-late colour) did not vary significantly with distractor timing (early or late). In other words, the feature-temporal likelihood of distractors did not significantly influence short-term performance for targets co-occurring with the respective distractors.

Several factors may underlie this null result. First, participants may not have learned the feature-temporal regularities strongly enough for them to influence behaviour. Methodological differences between this study and those in previous chapters could contribute to this. For instance, the task was more attentionally and physically demanding, requiring participants to filter stimuli in several colours and to respond continuously throughout each trial. The online format may also have reduced engagement. Moreover, unlike target responses, responses to distractors were discouraged, removing motor scaffolding that potentially supported regularity learning (see Chapter 3). Finally, distractors were presented in waves of three, rather than individually. These broader temporal windows associated with the regularities potentially made learning more difficult.

Beyond methodological differences, the fact that the regularities concerned distractors rather than targets may itself have impeded learning. While participants are encouraged to attend to targets, they are instructed to avoid distractors. Disengagement with distractors may therefore have limited encoding of their regularities. Consistent with this, prior studies have found that participants failed to learn trial-to-trial regularities in distractor locations, even when equivalent regularities in target locations are successfully learned (A.-S. Li et al., 2023; H. Yu et al., 2023).

An alternative explanation is that participants *did* learn the regularities during the learning session, but this failed to influence performance under temporally likely versus unlikely distraction in the testing session. One possibility is that participants' inhibitory control was sufficiently strong to override prediction violations in the moment, enabling consistent target performance regardless of distractor likelihood. Alternatively, the immediate disruptive effects of distractors may have been so

pronounced, even during the testing session, that any modulation by temporal predictions was too subtle to detect, resembling a floor effect.

It is also possible that any performance effects due to learnt predictions were rapidly extinguished by early exposure to temporally invalid distractors. Prior research has shown that learnt suppression of likely distractor colours (Golan & Lamy, 2022) and locations (Di Caro & Della Libera, 2021) decays quickly once probabilities are equalized, in contrast to more persistent effects of target-based learning (B. A. Anderson et al., 2021). Although the present study's testing session did not fully neutralise the regularities (with 75% of distractor waves still appearing at their likely time), experiencing even a few invalid trials may have triggered fast extinction of any learnt suppression, making effects difficult to detect across the session.

Although the testing session analysis revealed no significant *short*-term effects of distractor validity on performance, it did provide evidence for *longer*-term effects of valid versus invalid early distraction. When performance for both early *and* late targets were considered, early distractors slowed RTs more overall when they appeared in the likely-late colour compared to the likely-early colour. While this difference was numerically more pronounced for targets presented later in the trial (Figure 4.3C&D), there was no significant interaction with target onset window. This suggests that the performance benefit for temporally expected early distraction was statically similar across both early and late targets.

In contrast to the earlier null results for testing session targets appearing concurrently with distraction, this finding challenges the conclusion that participants failed to learn the task regularities. Instead, it suggests that this learning may have influenced behaviour in more nuanced ways than hypothesised. To speculate, encountering an unexpectedly timed distractor colour early may have required participants to allocate cognitive resources to processing this suppressing event and

updating internal predictions in the seconds that followed, slowing the recovery of performance in the main task.

An alternative hypothetical explanation for the longer-term effects of valid versus invalid early distraction is that participants used the *colour* of distractors as a cue to infer the current *time* within a trial. This would represent a kind of reversed causal inference based on the regularities from the assumed direction of prediction. If so, encountering distractors in the likely-late colour may have led participants to anticipate the trial's end. When the trial continued, because the distractors had in fact appeared early, participants may have been unprepared to continue and thus responded more slowly to subsequent targets. This account would align with the observed, albeit non-significant, interaction trend of greater performance differences between trials with valid and invalid early distractors for targets appearing *late*.

Overall, the results of this *testing session* analysis suggest that participants did form some predictions relating to distractor colours. However, I cannot conclude with certainty that these predictions were truly *feature-temporal* in nature. Instead, it is possible that participants simply expected that all distraction was more likely to occur in the likely-early colour than the likely-late colour, regardless of timing. To demonstrate temporal specificity, it would be necessary to show that the longer-term performance deficit observed for likely-late versus likely-early colour distractors appearing *early* was either absent or reversed for distractors appearing *late*. Unfortunately, such a comparison is not possible here as late distractors appeared close to the end of trials, preventing the analysis of post-distraction target performance. That said, logic based on the overall statistics of the task supports a temporally specific account. Across all trials, distractors were equally likely to appear in either colour, regardless of timing. Therefore, there was no rational basis for participants to expect one distractor colour more than the other in general. This makes it more plausible that the

performance deficits following likely-late coloured early distraction reflected violations of predictions about both the timing *and* colour of the distractors, rather than colour alone.

My second approach to investigating feature-temporal distractor predictions involved comparing performance for targets in similar colours to either distractor. Preliminary analyses showed that, during the *learning session*, performance was consistently worse for targets in a distractor-similar colour compared to targets with an equidistant colour between the two distractor colours. This could suggest that participants' internal representations of distractor colours were not sharply tuned to their exact hues. Instead, any learnt handling of distractor colours may have (partially) generalised to adjacent colours, reminiscent of 'spillover' effects for stimuli at locations neighbouring a predictable salient distractor location (B. Wang & Theeuwes, 2018).

It should be acknowledged that this pattern of results may reflect frequent confusion between some target and distractor colours. Though Data Cleaning excluded participants whose performance strongly indicated such confusion, some degree likely remained in the final sample. As noted previously, this could have impaired participants' ability to learn the task regularities, as mistaking temporally unpredictable targets for distractors would reduce the apparent temporal predictability of the distractor colours. However, the hit rate deficit for distractor-similar versus neutral targets decreased substantially by the final learning block (Supplementary Figure 7.15B), suggesting that participants became better at distinguishing between targets and distractors over time and thus may still have had sufficient opportunity to learn the regularities.

Although the use of similar target and distractor colours may have caused confusion, it also enabled temporal tuning of feature-based search behaviour to be investigated in the absence of actual distractors. This investigation revealed that, during distraction-absent learning trials, targets similar to the likely-early distractor colour were hit significantly less than those similar to the likely-late distractor colour, only when targets onset early. This suggests that, as hypothesised, participants

dynamically modulated their avoidance of certain hues throughout trials according to the task's regularities. Because this effect emerged in the absence of distraction, changes between early and late times likely reflect participants tracking time within the trial, rather than reacting to distractor appearances. Notably, the effect did not interact significantly with block number, which could imply either rapid learning or flag that it was not driven by regularity-based learning.

The performance benefit for target colours similar to the temporally unlikely, versus likely, distractor colour being specific to *early* targets may reflect greater learning of regularities about early compared to late distractors. This could align with the previous finding that *d'* scores were consistently higher for early compared to late stimuli in distractor-present learning trials. The increased sensitivity at early times may have enabled participants to better learn the distractor-based regularities at this time. Prioritising learning about early distractors may also have been an adaptive strategy given that early distraction, unlike late distraction, could impair performance collecting both early *and* late targets, thus exerting a potentially greater impact on overall performance. This pattern of temporal specificity also aligns with Chapter 2 findings, where effects of target-based feature-temporal predictions on DVS performance were strongest early in the trial.

These findings, showing changes in performance for different target colours based on distractor expectations, relate to research on target template tuning. Previous studies, using both static and dynamic search tasks, have shown that internal representations of target features are adjusted based on the expected distractor context to maximise target to distractor distinctiveness, leading to relational feature-based guidance (e.g., Boettcher & Nobre, 2025; Geng & Witkowski, 2019; Grössle et al., 2023). The present results tap into the question of whether such template tuning can operate in a dynamic, adaptive manner when expectations about distractors vary predictably with time during search. Future work could more systematically probe how attentional templates evolve during search in contexts where distractor features change predictably over time.

What remains unclear is whether the observed effects relating to target colour reflect a temporally tuned *increase* in avoidance of likely-distractor-similar hues, a *decrease* in avoidance of unlikely-distractor-similar hues, or both. Preliminary analyses (Supplementary Figure 7.15A) showed that, relative to neutral targets, both types of distractor-similar targets were avoided at both early and late times. However, the present task design lacks a baseline condition that would allow assessment of transient increases or decreases in the extent of this avoidance. Future studies could address this by measuring performance for targets similar in colour to a distractor that is temporally unpredictable.

While much prior work has emphasised suppression of distractor features, these findings may instead reflect enhancement of expected target features. Previous work suggests that apparent distractor suppression effects may in fact arise from increased attention to target features (Noonan et al., 2018; Oxner et al., 2023, 2024). If attentional templates were indeed tuned away from the likely-early distractor hue at early times during trials, and thus tuned toward the likely-late distractor hue, this could explain the relative advantage for targets in that colour without the need for attentional suppression. Alternatively, both suppression and enhancement mechanisms may have operated concurrently (Andersen & Müller, 2010; Navalpakkam & Itti, 2007).

Another limitation of the study is that it cannot conclusively attribute the observed performance effects to perceptual attentional guidance. While the results are consistent with temporally tuned shifts of feature-based attention away from likely distractor colours, they could also reflect modulations at the level of decision-making or response processes. For instance, participants may have been more likely to misclassify a target similar in colour to the likely-early distractors if it also appeared at the time these distractors were expected, choosing not to collect it and perhaps inhibiting any prepotent response. Thus, the reduction in hits for these targets at early times during trials may reflect feature-temporal shifts in decision criteria or response inhibition, rather than

perceptual attentional suppression. Future studies could incorporate eye-tracking measures, as in Chapter 2, to better disentangle early attention-based effects from those driven by later-stage processes.

Overall, the performance impairments associated with temporally unlikely early distractors in the testing session, together with the temporal tuning of performance for distractor-similar target colours in the learning session, suggest that participants learnt the feature-temporal regularities associated with (early) distractors to some extent. Speculatively, the RT effects in the testing session may reflect surprise triggered by violations of internal predictions about distractors, whereas the hit rate effects in the learning session may indicate more active use of these predictions to guide task behaviour.

Contrary to expectations, participants were not better at shielding target performance against incoming distractors when their colour was temporally expected. Instead, effects of learnt predictions were clearer for targets that appeared in the absence of distraction. A possible reason for this relates to the task's scoring system. Collecting a distractor resulted in a larger penalty (-10%) than the reward for collecting a target (+5.26%). This may have led participants to adopt a more conservative strategy, maintaining a consistent level of distractor avoidance and instead using feature-temporal predictions to adjust which distractor-similar targets to forgo. In other words, they may have opted to miss some targets resembling temporally likely distractors, rather than to risk collecting temporally unlikely distractors. Future studies could also explore how manipulating the relative costs and rewards for targets and distractors influences learning of distractor-based regularities during dynamic search. For instance, if false alarms had no cost, participants may have engaged with distractors less, hindering learning (though see Duncan et al., 2025).

Although the present study did not find robust evidence for effects of feature-temporal predictions on the immediate handling of incoming distraction, this does not rule out the possibility

that such effects could emerge in a different paradigm. For example, stronger effects may arise with more extensive learning, or within a less demanding task. It would be informative to investigate whether participants can learn to suppress temporally likely distractor features in a more controlled and well-established paradigm, such as the additional-singleton task, potentially paralleling previous findings for spatiotemporally predictable salient distractors (Xu et al., 2021).

4.6 Conclusion

This chapter used a tablet-based DVS task with multiple temporally unpredictable targets to investigate how feature-temporally predictable distraction influences performance over time. The findings suggest that participants were at least partially able to learn temporal regularities in distractor colour. Although this learning did not significantly affect short-term handling of distractors, it had secondary effects on performance: shaping post-distractor recovery, as well as responses to distractor-similar targets in distractor-absent trials. As research into mechanisms of suppression continues to grow, this work highlights the importance of considering the role of temporal regularities in guiding distractor handling within dynamic, real-world environments.

5 General Discussion

Real-world visual search rarely unfolds in fully static contexts. Instead, it must contend with temporal shifts in the environment, such as when items appear and disappear from view. Just as spatial and feature-based regularities can guide behaviour between locations and items, *dynamic* visual search may also benefit from regularities operating across time. Yet, our general understanding of how temporal expectations affect visual search is limited, and the specific influences of feature-temporal regularities, that is, predictable associations between stimulus features and timing, have been largely unexplored.

My doctoral thesis addresses this gap by examining how feature-temporal regularities affect search in dynamic displays where stimuli appear across times and locations with spatial and ordinal uncertainty. In doing so, this work advances research on temporal expectations in visual search and contributes more broadly to the study of search within dynamic environments. In this final chapter of the thesis, I summarise the empirical findings, consider their wider implications, and outline future directions for investigating adaptive temporal shifts in visual search behaviour.

5.1 Summary of Empirical Findings

Chapter 2 provided initial evidence that target-based feature-temporal regularities systematically influence behavioural performance in dynamic visual search. Across two in-person experiments, participants searched for two targets whose associated features and responses were predictable in time. The results revealed an interaction between target onset time and expected onset. Specifically, targets that appeared early in the trial were identified more efficiently when their appearance matched expectations compared to when it violated them. To better understand the mechanisms underlying these performance effects, I incorporated eye tracking (Experiments 1 and

2) and EMG (Experiment 2) measures to probe the contributions of visual attention and motor preparation. Eye-tracking patterns differed between experiments, suggesting sensitivity to trial structure. However, the results of Experiment 2 (where the gap separating early and late targets was extended) indicated that learning of feature-motor-temporal regularities *can* dynamically modulate both attentional capture to temporally predictable target features and preparatory muscle activity for target-specific responses.

Chapter 3 extended this work by investigating whether feature-temporal regularities and motor-temporal regularities can guide behaviour not only in combination, as found in Chapter 2, but also in isolation. In a large-scale online experiment with over 250 participants, each observer was exposed to one of four types of target regularity: purely temporal, feature-temporal, motor-temporal, or feature-motor-temporal. Relative to the neutral temporal-only baseline, some degree of performance benefit emerged for each of the expectation conditions, though effects were weakest for feature-temporal regularities. In contrast to Chapter 2, there was no reliable evidence of performance costs when targets occurred at their unlikely times. Overall, these findings suggest that feature-temporal and motor-temporal regularities are likely to facilitate dynamic visual search independently as well as in combination, though the reliability of these effects may vary across contexts.

Chapter 4 shifted focus to examine whether feature-temporal regularities in distractors rather than targets influence search. Participants collected temporally unpredictable, variably coloured targets while avoiding two distractor colours that appeared predictably early or late in a trial. Immediate effects of distractors on performance were not significantly influenced by whether their colour was temporally likely or unlikely. Instead, the feature-temporal regularities had more downstream effects on behaviour. Performance was impaired following early distraction when its colour was temporally unlikely. In addition, participants' avoidance of distractor-similar targets varied

over time according to which distractor colour was temporally expected. These findings suggest that feature-temporal regularities *can* be extracted even when tied to distractors rather than targets, although their influence on performance may be more nuanced.

5.2 Visual Search is Dynamic and Biased by Feature-Temporal Predictions

5.2.1 General Effects of Time-in-Trial

A key finding across chapters is that visual search behaviour changes over time *within* a trial. While previous research has examined temporal dynamics of search-related processes across the lifespan (e.g., Humphrey & Kramer, 1997; Trick & Enns, 1998), across experimental trials (e.g., Geng & Behrmann, 2005; Sha et al., 2017), and during preparation for search (e.g., Grubert & Eimer, 2018, 2023), fewer studies have addressed how behaviour shifts *within* an extended search episode.

Although not the primary focus of this work, general time-in-trial effects emerged across experiments. For example, in Chapter 2, distractors appearing later in a trial were overall more likely to be fixated than those appearing earlier – highlighting how eye-movement patterns may shift across time during extended search. In Chapter 3, targets were identified more efficiently when they appeared late rather than early. Yet, in Chapter 4, sensitivity for collecting targets over distractors was higher for stimuli appearing early than late. This difference may be due to a shift in target collection behaviour. In Chapter 3, participants needed to find a maximum of two targets, so their search efficiency may have been subject to changing expectations due to the hazard rate. However, in Chapter 4, participants were collecting targets throughout the trial, and so the shift in behaviour may reflect fatigue. Irrespective of their underlying causes, these effects illustrate that visual search behaviour can vary as a function of time spent searching.

These findings relate to foreperiod studies that have examined how delay length influences subsequent performance in static visual search (e.g., Grubert & Eimer, 2018; Seibold & Rolke, 2014).

Importantly, the current studies can explore within-episode timing in unique ways compared to empty foreperiod delays, due to their dynamic nature. This supports the view that the factors guiding search are time-sensitive, with attentional priority maps evolving continuously throughout a search episode (Liesefeld et al., 2024; Noonan & Störmer, 2023; Wolfe, 2021). While prior discussions of priority map dynamics have often focussed on the temporal profiles of underlying cognitive processes, such as the latency of distractor suppression (Beck et al., 2018; Zhang et al., 2025), the present findings suggest that the *passage of time* itself can modulate these processes in turn and shape behaviour on a broader scale.

5.2.2 Adaptive Modulation by Feature-Temporal Regularities

Beyond unstructured time, the central contribution of this thesis is the demonstration that visual search can be systematically and adaptively biased by structured *feature-temporal regularities*. Specifically, in Chapter 2, task performance and feature-based attentional capture were biased toward temporally expected targets. In Chapter 3, targets that were predictable across feature and time, as well as those predictable across feature, time, and response, yielded performance benefits. In Chapter 4, performance was biased away from targets resembling temporally expected distractors, and feature-temporally expected distractors resulted in a reduced cost on subsequent performance. Importantly, across these studies, the relevant events were equally likely overall: early and late time points occurred equally often, as did the relevant colours. It is only when pairing time and features that predictability emerges. This indicates that these effects reflect *time-dependent shifts in feature-based biases*, rather than more general modulation of feature or temporal processes independently.

Crucially, I found evidence for dynamic tuning under spatial, motor, and ordinal uncertainty. Prior studies of temporally contingent search modulation have focussed on spatial shifts (Boettcher et al., 2022; Shalev et al., 2022, 2024; Xu et al., 2021, 2023). By contrast, in this thesis stimuli appeared unpredictably across a wide a range of spatial locations with features instead scaffolding the temporal

predictions. In Chapters 3 and 4 these effects were established without a predictable response mapping. These findings extend related work showing effects of predictable feature-time associations in different task contexts (Echeverria-Altuna et al., 2024; Gao et al., 2025; Thomaschke et al., 2016; Wagener & Hoffmann, 2010) by demonstrating that observers can extract feature-temporal regularities across competing items in space and time to influence visual search specifically.

Regarding ordinal uncertainty, observers extracted feature-temporal regularities across an unpredictable number of preceding stimulus appearances. It is worth noting that, in all studies, participants did experience two feature-temporally predictable events suggesting they could have encoded a relative, ordinal representation of features associated with early and late events. However, because the reported effects of regularity-based temporal modulation were found in trials with only one or even zero predictable events, these effects appear to have arisen from participants tracking time itself, rather than simply exploiting ordinal associations. In addition, in Chapter 2, effects were sensitive to the different timings across Experiments 1 and 2, with slightly different eye-movement patterns emerging with longer timings. If these effects were purely "ordinal", it is unlikely that this difference in timing would have affected these results. Future work should however confirm whether direct exposure to ordinal associations between temporally predictable events (as in two-target trials here) provides necessary scaffolding for the learning and use of associated temporal regularities.

Finally, general time-in-trial effects and effects due to feature-temporal regularities are likely to interact. Improved performance at a given point in a trial may reflect more effective use of regularities tied to that time. Conversely, regularities may be learned or applied more effectively because performance is enhanced at those moments. Clarifying these interactions will help distinguish independent effects of unstructured time and structured temporal learning.

5.2.3 Implications for Priority Maps

Overall, this empirical work supports the view that priority maps are not only dynamic but can develop temporal structures that reinitiate at the beginning of each search episode. These structures are not necessarily spatially anchored and can become biased toward time-dependent regularities across repeated episodes in a given context, even if observers are unaware of these regularities beforehand. These maps may help overcome visual processing limitations by continually guiding attention between relevant features in a flexible manner. In dynamic contexts, such adaptive guidance may be essential for maintaining search efficiency, requiring biases not only to features relevant at the start of search but also to those that become relevant as time unfolds.

5.2.4 Future Directions

Several open questions remain. Future work could test the limits of learning here by examining whether observers can acquire and use feature-temporal regularities for features other than colour, and how this may depend on the precision of visual discrimination required for that feature, or the ability of that feature to guide attention. Further, future investigations could test whether feature-temporal regularities can influence behaviour when they concern features that are not directly task-relevant. In the present studies, all regularities involved task-relevant features: across chapters, they distinguished targets from distractors, and, in Chapter 2, they also defined responses. Prior work with foreperiod tasks has suggested that predictable time-feature associations benefit performance only when the features are directly task relevant (Thomaschke et al., 2016; Thomaschke & Dreisbach, 2013), whereas visual search research has shown that observers are sensitive to non-temporal regularities in task-*irrelevant* features (Sha et al., 2017). Whether predictable associations between timing and incidental features can bias search remains an open question.

Another promising direction is to investigate how different forms of *temporal uncertainty* may affect the strength and time course of resultant behavioural shifts. In this thesis, regularities were always tied to fixed moments in time. If relevant onsets instead varied according to a particular distribution, it would be informative to test whether the dynamics of search behaviour mirrored that distribution. Such work may provide a temporal parallel to findings that attentional biases in visual search are sensitive to the learned variance of feature values (Chetverikov et al., 2019; Witkowski & Geng, 2019).

5.3 Multiple Search Processes Can Be Influenced by Temporally Contingent Regularities

Another key takeaway of this thesis is that performance benefits from temporally contingent regularities can be attributed to modulations of multiple different component processes.

5.3.1 Perceptual, Motor, and Decision-Related Processes

Both perceptual and motor-related mechanisms can be temporally tuned. In Chapter 2 (Experiment 2), eye-tracking data revealed increased attentional capture by temporally expected target features, while EMG data showed enhanced motor preparation for temporally expected responses. In Chapter 3, predictable associations between target timing and features, and between target timing and motor responses, each independently improved performance to some degree. In Chapter 4, early targets similar in colour to temporally expected distractors were missed more often than those similar to temporally unexpected distractors, possibly reflecting shifts in feature-based attentional avoidance. These insights complement prior work showing that location-based stimulus processing, and possibly directional saccade preparation, can also be dynamically modulated by spatiotemporal regularities in visual search (Boettcher et al., 2022; Xu et al., 2021, 2023).

Notably, feature- and motor-based temporal tuning may support different aspects of search performance. Supplementary analyses in Chapter 3 suggested that motor-temporal regularities

primarily influenced response times rather than accuracy. This aligns with the intuitive distinction that feature-based attentional modulations may influence sensitivity to the target, while motor-based modulations more directly influence response speed. However, this possible division requires further investigation. The utility of perceptual versus motor modulations may also depend on task demands (Arrouet et al., 2025; van Ede et al., 2020). For instance, feature-temporal regularities may be most advantageous in perceptually demanding tasks, such as those with substantial target-distractor similarity or high feature variability (J. Duncan & Humphreys, 1989), whereas motor-related regularities may provide greater benefits when tasks emphasise speeded responses.

Beyond early attentional selection, an open question not addressed in this thesis is how feature-temporal regularities influence later verification processes, when observers decide whether a stimulus is a target and perform a response (see Wolfe, 2020). Temporal expectations have been shown to modulate neural signatures of decision-related processes in non-search tasks (Gao et al., 2025; van den Brink et al., 2021). Of relevance, Gao et al. (2025) reported that predictions about feature-time associations in an RSVP task modulated EEG markers of late decision processes without affecting markers of target selection. However, the eye-tracking results from Chapter 2 (Experiment 2) suggest that fixational stimulus selection can be modulated by feature-temporal predictions in a competitive, dynamic visual search task. Whether decision-related processes are similarly affected in such contexts remains an interesting avenue for future research. While the present thesis focussed on fixation analyses, additional eye tracking measures, such as the interval between an initial fixation on a target and a manual response, could provide further insight here (Hollingworth & Bahle, 2020).

5.3.2 Interactions with Goal-Driven Control

A key consideration in understanding how feature-temporal predictions impact visual search is their interactions with other sources of attentional guidance. This thesis highlights this with respect to goal-driven attention. While feature-temporal predictions modulated the relative extent to which

participants engaged with different stimulus features over time, a notable and robust finding was that goal-driven control remained dominant across extended trials.

In Chapter 2, stimuli in the likely-early or likely-late target colour were consistently more likely to be fixated than stimuli in the non-target colour regardless of timing, indicating persistent goal-driven prioritisation of both target colours. Similarly, in Chapter 4, supplementary analyses showed that targets similar in colour to either likely-early or likely-late distractors were collected less often than more neutral-coloured targets throughout trials, suggesting sustained avoidance of both distractor colours. These results indicate that learnt feature-temporal predictions may bias the relative weighting of attentional priorities but, overall, they do not override baseline goal-driven biases within these tasks.

It is worth noting that this pattern reflects averaging across participants who may have learnt and used the regularities to different extents. Future work could nevertheless test whether stronger temporal predictions might yield more extreme modulations overall, temporarily eliminating goal-driven prioritisation of certain features when they are temporally unexpected.

This pattern adds nuance to recent findings on interactions between time-independent feature-based expectations and goal-based attentional templates. Grubert and Eimer (2023) investigated the activation of templates for each of two colour-defined targets prior to visual search by measuring neural responses to colour probes. Even when the two target colours appeared with different probabilities, the relative activation of their templates prior to search was unaffected, indicating equivalent activation of goal-driven attention to both likely and unlikely target colours (see also Beck et al., 2012). However, during search, subsequent target selection processes were strongly influenced by these probabilities. The present work relates to these findings by suggesting that goal-driven attention remained dominant for both temporally likely and unlikely features, while their relative likelihoods still produced measurable modulations. Together, these works highlight the

complex interactions between goal-driven control and feature-based predictions, which themselves may evolve over the course of a trial.

5.3.3 Target and Distractor Regularities

This thesis also examined how feature-temporal regularities modulate component processes of dynamic visual search through the dynamic upweighting and downweighting of task-relevant features. Observers extracted and used regularities tied to both targets and distractors. Chapters 2 and 3 showed adaptive shifts in behaviour consistent with anticipating temporally likely *target* features. In Chapter 4, participants expected certain *distractor* colours at specific times during trials and these expectations modulated behaviour, albeit less directly. Using feature-temporal regularities to guide behaviour may therefore help maintain adaptive biases both toward rewarding target features and away from costly distractor features as search unfolds. This complements previous findings that spatiotemporal regularities can both bias attention toward temporally likely target locations (Xu et al., 2023) and away from temporally likely distractor locations (Xu et al., 2021) in static, singleton search.

Beyond these independent effects, a notable insight is that feature-temporal regularities associated with one class of item influenced handling of the other class. In Chapter 2 (Experiment 2), target-based regularities dynamically modulated how distractors that shared target features captured attention. In Chapter 4, distractor-based regularities affected avoidance of targets that resembled distractors.

An open question, and a limitation of this work, is whether the behavioural shifts observed in Chapter 2 reflect a relative upweighting of temporally expected target features, a relative downweighting of temporally unexpected target features (which were temporally more likely to be distractor features), or both. While it is of note, when comparing the temporally unexpected target to the third *non-target* colour there is still an overall higher rate of fixations, the underlying cause of

the relative difference between temporally expected and unexpected target features cannot be discerned. Relatedly, it is unclear whether the modulation observed in Chapter 4 reflects primarily a downweighting of the temporally expected distractor feature or a relative upweighting of the temporally unexpected distractor feature (see Andersen & Müller, 2010; Noonan et al., 2018; Oxner et al., 2023, 2024). Future studies could address this issue by comparing how biases toward temporally likely and unlikely features change relative to a temporally unpredictable baseline feature that is equally task-relevant (e.g., by introducing a temporally unpredictable target colour in Chapter 2).

In summary, the work in this thesis indicates that temporally contingent regularities can exert multidimensional influences on the component processes of dynamic visual search, modulating perceptual and motor processes as well as the upweighting and downweighting of target and distractor attributes. Future work should examine how additional processes, such as decision-related mechanisms, are affected, and how interactions or transfer between these different forms of modulation may unfold.

5.4 Methodological Advances and Challenges in Studying Dynamic Visual Search

5.4.1 Advancing Dynamic Search Tasks and Measures

While the central theoretical aim of this thesis was to understand how regularities across features and time can guide behaviour, addressing this aim posed methodological challenges. Traditional search tasks typically reduce behaviour to a single trial-level measurement, such as reaction time or accuracy, offering limited insight into how performance evolves within a trial. To overcome this, I developed extended dynamic visual search tasks in which stimuli appeared transiently at staggered times across longer trials, building on the dynamic tasks developed by Boettcher et al. (2022). These tasks were complemented by continuous measures of eye movements,

muscle activity, and ongoing performance, providing more temporally precise insights into how behaviour unfolds over time.

In Chapter 2, EMG recordings continuously tracked motor preparation, while distractor fixation data indexed the extent to which target features captured attention across time. This parallels Grubert and Eimer's (2018) approach of probing feature-based attention via neural responses to non-target probes to track the time course of attentional processes *prior* to search. Here, however, modulations were measured during search itself and using search stimuli rather than additional probes. This method helps to preserve a more naturalistic task context. In Chapter 4, a tablet-based task collected temporally sensitive data by presenting many targets continuously throughout the trial. Drawing inspiration from foraging tasks (e.g., Grössle et al., 2023; Tünnermann & Schubö, 2025), this design demonstrates how such methods can be adapted for online testing. Indeed, through this design I was able to dissociate both the immediate and downstream effects of distraction, an insight that would not have been possible without repeatedly sampling behaviour.

Together, these approaches represent a methodological advance: continuous tasks paired with temporally sensitive measures. This moves beyond traditional single-trial metrics to reveal the dynamics of search as it unfolds in more naturalistic settings.

5.4.2 Practical Challenges and Limitations

Despite these advantages, dynamic search tasks also pose challenges. The extended trials increase participant fatigue and limit the number of trials that can be run in an experimental session, reducing statistical power. This is particularly problematic for statistical learning studies, which require repeated exposures to regularities. Moreover, while staggered event onsets within a trial provide richer temporal information compared to static displays, measurements remain discrete, and high trial numbers are needed to obtain high-resolution time courses of behavioural change. One potential solution for future studies is to distribute experiments across multiple shorter sessions,

which can ease participant burden and, in some cases, support learning (e.g., Cepeda et al., 2006; Lerner & Gluck, 2022).

These challenges are amplified in online testing as seen in Chapters 3 and 4, where exclusion rates were high. The long and attentionally demanding sessions likely reduced engagement and pose concerns for online data quality (Sauter et al., 2020). In addition, the tasks relied on fine visual discrimination of stimulus features, which is vulnerable to variability in participants' display settings and lighting conditions. While the game-like quality of the tasks made them appealing for online use, these factors suggest that extended dynamic tasks of this type may be better suited to controlled in-lab settings.

5.4.3 Natural Dynamics

Real-world search environments are inherently richer and more complex than traditional laboratory experiments. To bridge this gap, researchers have increasingly developed dynamic visual search tasks (e.g., Bennett et al., 2021; Boettcher & Nobre, 2025; T. Kristjánsson et al., 2022; Muhl-Richardson, Godwin, et al., 2018; Nuthmann & Canas-Bajo, 2022). Although not always designed with this purpose in mind, such tasks are particularly well suited for studying temporal expectations, which are themselves dynamic in nature (Nobre & van Ede, 2023). The experiments in this thesis adopted dynamic designs while remaining highly controlled and used abstract stimuli to isolate effects of feature-temporal regularities, striking a balance between ecological fidelity and experimental control. However, future work should explore whether such regularities guide search effectively in more complex environments, such as those involving stimulus motion or immersive three-dimensional scenes that allow participant-driven exploration.

Moreover, temporal expectations in natural settings often rely on semantic knowledge – for instance, anticipating that cars arrive before pedestrians, or that people will move through a scene while furniture remains still (Draschkow & Võ, 2017; Võ & Wolfe, 2015). Temporal expectations can

also unfold across longer timescales than typical laboratory studies: concerning intervals more than a few seconds and building up across exposures to regularities over days or years, rather than a single session. The extent to which regularity-based temporal predictions can guide search across such timescales remains unclear. However, it is possible that increasing the delay between predictable events (as in Chapter 2) and extending learning repetitions across longer periods (Smith & Scarf, 2017) may strengthen internal representations of likely timings. Finally, search in natural settings rarely begins with the abrupt onset of a display. By extension, temporal expectations are more likely to be derived relative to other continuously unfolding events rather than to display onset. Future research should consider how temporal predictions operate in continuous contexts, rather than during trial-based structures (Zacks & Swallow, 2007).

Recognising that performance can be influenced by feature-temporal regularities has implications for applied dynamic visual search contexts. These range from the design of interactive digital displays (Jokinen et al., 2020), to safe driving (Chapman et al., 2002), to how air traffic controllers monitor flights (Remington et al., 2000). Studying these influences in real-world settings is therefore important for identifying both the benefits and risks of observers adapting their behaviour to temporal regularities when relevant events uphold and violate associated expectations, respectively.

5.5 Final Conclusions

Finding goal-relevant targets amongst distractors is a fundamental aspect of everyday behaviour. While visual search has most often been studied in static contexts, real-world environments are dynamic, requiring guidance to adapt over time. This thesis provides early evidence that such adaptation can be shaped by feature-temporal regularities, whereby the features of task-relevant items can be predicted based on their time of appearance.

Across three empirical chapters, I showed that behaviour within a single search episode is dynamic and can be systematically modulated over time by learnt feature-temporal regularities, even under spatial uncertainty. Temporally-contingent regularities influenced both perceptual and motor mechanisms and affected the handling of both targets and distractors during visual search. Methodologically, I introduce novel dynamic tasks and measures that can track the evolution of feature-based biases within visual search episodes.

Overall, this thesis demonstrates that visual search can be directed between non-spatial features over time in accordance with predictable temporal structures in our environments. This highlights the flexibility with which humans can extract and exploit regularities in complex dynamic contexts. Future research should extend these approaches to richer, more naturalistic settings to better understand how temporal predictions support adaptive behaviour in the real world.

6 References

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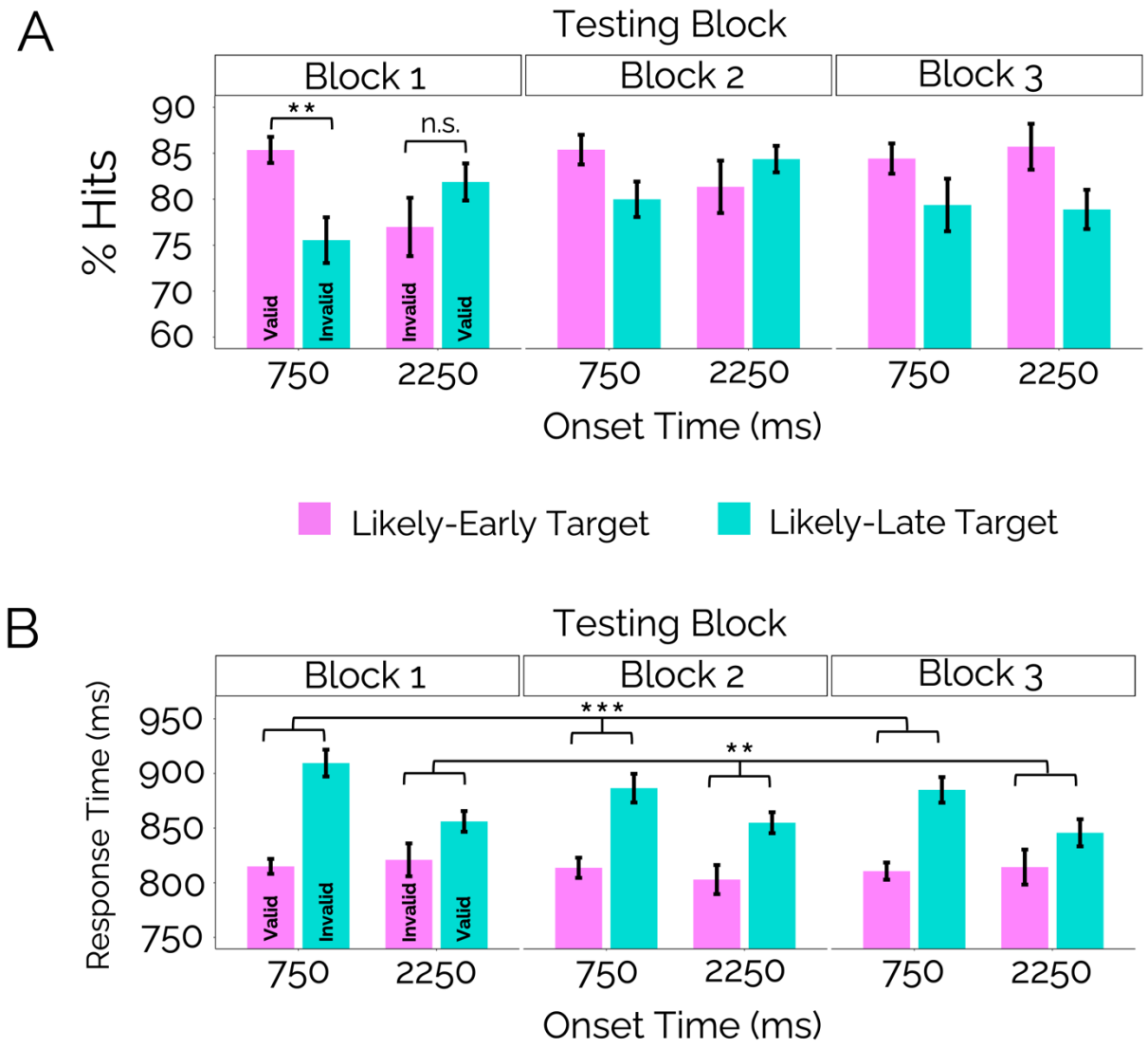
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7 Appendix

7.1 Supplementary Materials for Chapter 2



Supplementary Figure 7.1. Chapter 2 (Experiment 1). (A) Mean (untransformed) percentage hits for identifying targets in each block of the testing session in Experiment 1, for likely-early and likely-late targets appearing at each onset time. Here, and in all subsequent supplementary figures, error bars represent ±1 standard error (SE) around the mean. A 2x2x3 ANOVA analysing the effects of target likelihood, onset time, and block number on hits (with hits having undergone a square transformation in line with *boxcox* recommendations) revealed a significant two-way interaction between onset time

and target likelihood (p = .024) and a significant three-way interaction between these two variables and block number (p = .008). No other predictors were significant. The full output of the hits ANOVA is shown in Supplementary Table 7.1 below. Three follow-up 2x2 (onset time x target likelihood) ANOVAs analysing hits data from each testing block (with Bonferroni-corrected significance level .017) revealed that the two-way interaction between onset time and target likelihood was significant in the first testing block (F(1, 23) = 9.37, p = .006, η^2 = .053), but not in block 2 (F(1, 23) = 3.67, p = .068, η^2 = .022), or in block 3 (F(1, 23) = 0.94, p = .342, η^2 = .003). Two additional t-tests analysed the effect of target likelihood at each onset time in testing block 1. Consistent with better performance identifying temporally likely versus unlikely targets, when targets onset at 750 ms, participants hit significantly more likely-early targets (M = 85.36%, SD = 10.05%) than likely-late targets (M = 75.55%, SD = 10.05%; t(23) = 3.42, p = .002, d = 0.69, BF_{10} = 16.55). When targets onset at 2250 ms, target likelihood had no significant effect on hits (t(23) = -1.00, p = .328, d = -0.23, BF_{10} = 0.34). **(B)** Mean (untransformed) response times (RTs) for identifying targets in each block of the testing session in Experiment 1, for likely-early and likely-late targets appearing at each onset time. A 2x2x3 (target likelihood x onset time x block number) ANOVA (on log-transformed RT values) revealed a significant main effect of target likelihood on RTs (p < .001). Overall, participants were significantly faster to identify the likely-early target (M = 813 ms, SD = 35 ms) than the likely-late target (M = 869 ms, SD = 35 ms). Of interest, the ANOVA also revealed a significant interaction between onset time and target likelihood (p = .012). For targets that onset at 750 ms, the likely-early target (M = 891ms, SD = 69ms) was identified significantly faster than the likely-late target (M = 891ms, SD = 69ms), as revealed by a follow-up t-test (t(23) = -6.77, p < .001, d = -1.38, BF_{10} > 1000). A second follow-up t-test revealed that, while the RT difference between targets of each likelihood was reduced numerically when targets onset at 2250 ms, the likely-early target (M = 812ms, SD = 50ms) was still identified significantly faster than the likely-late target (M = 852ms, SD = 50ms; t(23) = -2.91, p = .008, d = -0.58, BF_{10} = 5.94). Full output of the ANOVA analysing RTs is shown in Supplementary Table 7.2 below. The statistical significance of follow-up comparisons is indicated in the figure with asterisks: *** = p < .001, ** = p < .01, n.s. = not significant.

Supplementary Table 7.1. Chapter 2 (Experiment 1)

Hits Main ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	0.01	1	23	.979	< .001
Target Likelihood	2.74	1	23	.112	.013
Block Number	1.78	2	46	.180	.006
Onset Time : Target Likelihood	**5.82**	**1**	**23**	**.024**	**.012**
Onset Time : Block Number	0.14	2	46	.869	< .001
Target Likelihood : Block Number	1.16	2	46	.321	.005
Onset Time : Target Likelihood : Block Number	**5.35**	**2**	**46**	**.008**	**.015**

Note. Here, and in subsequent supplementary tables, significant predictors are shown in bold.

Supplementary Table 7.2. Chapter 2 (Experiment 1)

RT ANOVA Output

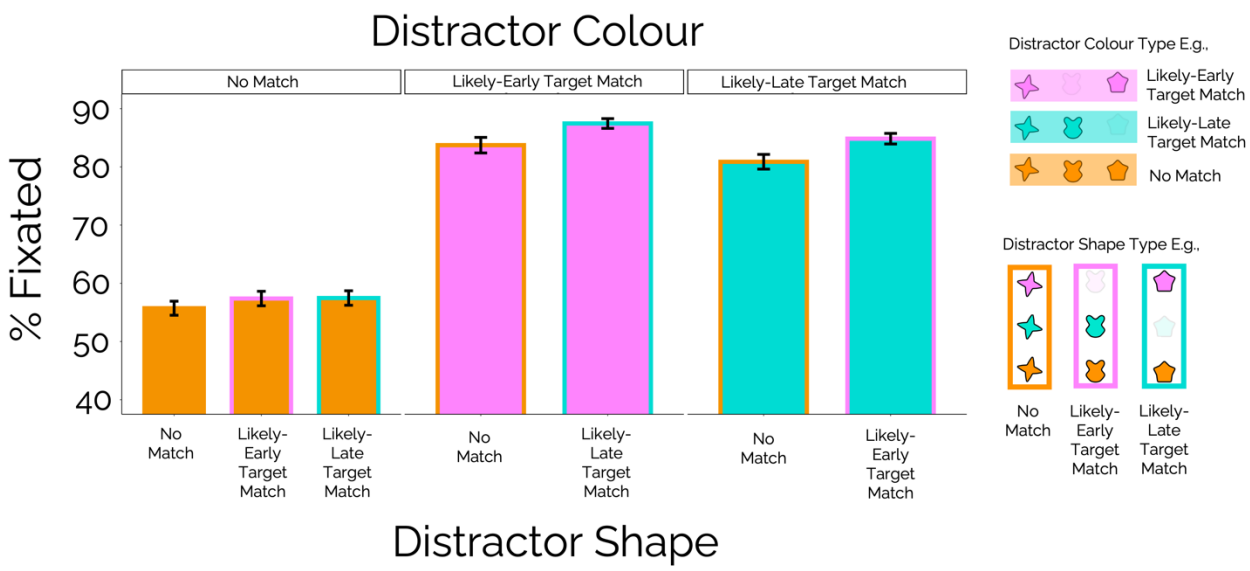
Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	**12.91**	**1**	**23**	**.002**	**.022**
Target Likelihood	**28.77**	**1**	**23**	**< .001**	**.155**
Block Number	2.23	2	46	.119	.006
Onset Time : Target Likelihood	**7.49**	**1**	**23**	**.012**	**.017**
Onset Time : Block Number	0.03	2	46	.967	< .001
Target Likelihood : Block Number	0.24	2	46	.790	< .001
Onset Time : Target Likelihood : Block Number	0.77	2	46	.471	.003

Supplementary Table 7.3. Chapter 2 (Experiments 1 & 2)

Colour Type (and Shape Type) Custom Contrasts for Distractor Fixations Analysis

	Goal-dependent Contrast (No Colour Match vs. Target Colour Match)	Prediction Contrast (Likely-Early vs. Likely-Late Target Colour Match)
No Match	1	0
Likely-Early Target Match	-0.5	-0.5
Likely-Late Target Match	-0.5	0.5

Note. The above contrasts were designed to explore two specific comparisons of the three levels of the colour type variable. The levels code whether a distractor shared its colour with neither target (No Match), the likely-early target (Likely-Early Target Match) or the likely-late target (Likely-Late Target Match). The first, 'goal-dependent', comparison (No Colour Match vs. Target Colour Match) compared distractors which did not share their colour with either target to those which shared their colour with any target. The second, 'prediction', comparison (Likely-Early vs. Likely-Late Target Colour Match) compared distractors which shared their colour with the likely-early target to those which shared their colour with the likely-late target. This contrast matrix was also used for preliminary and supplementary analyses using the shape type variable.



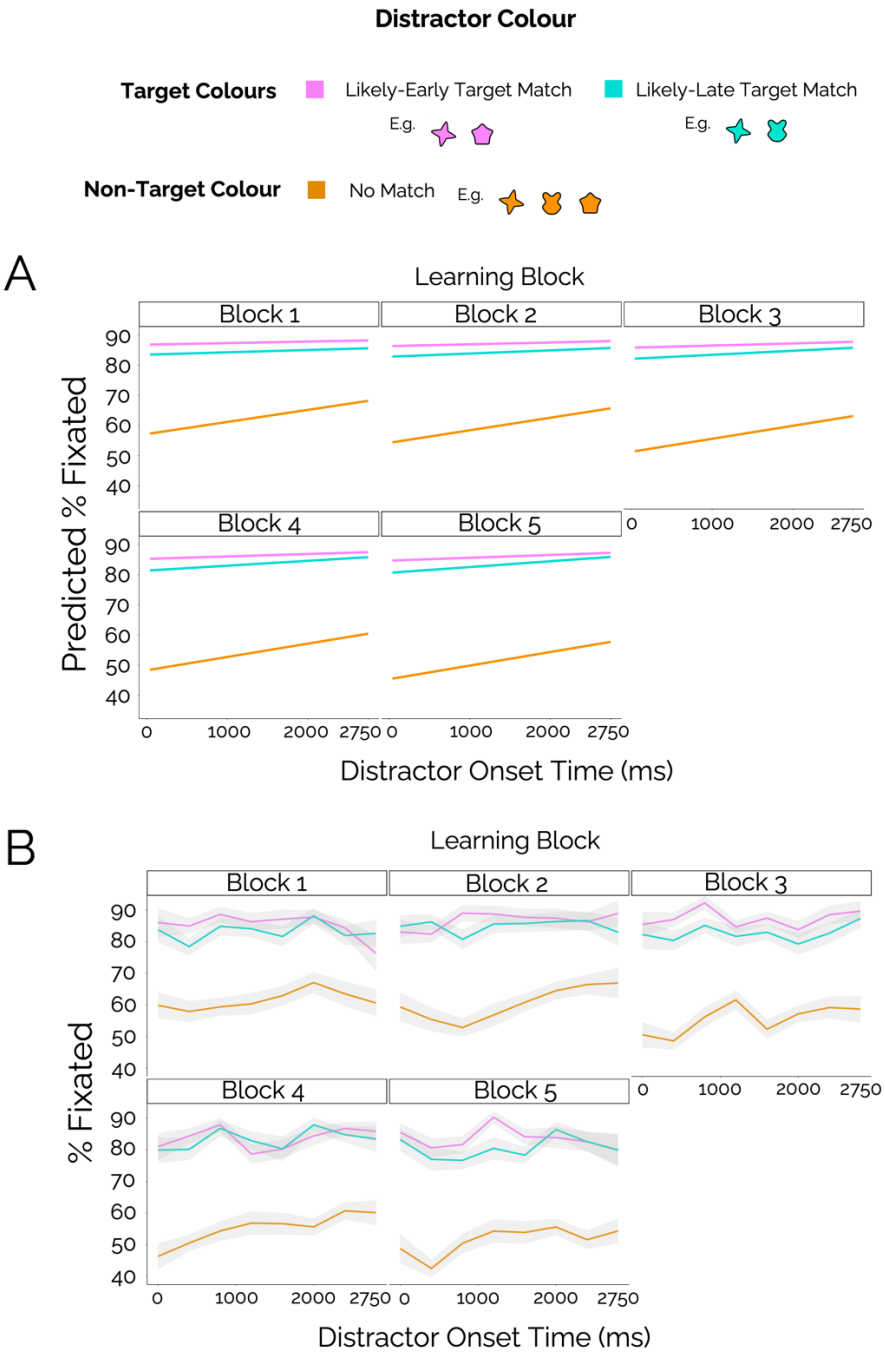
Supplementary Figure 7.2. Chapter 2 (Experiment 1). Mean percentage of distractors fixated across levels of colour type and shape type, for distractors from target-absent learning session trials in Experiment 1. Example distractors for each level of colour type and shape type for the example likely-early and likely-late targets are shown on the right. To investigate if participants used either target colour and/or target shape to guide their attention, a preliminary GLMM analysis investigated the overall effects of colour type and shape type, and their interaction, on fixation likelihood. Here, I focussed on effects of the goal-dependent contrasts, with the full optimal GLMM output given in Supplementary Table 7.4. The optimal GLMM had a fixed-effects structure containing colour type, shape type, and their interaction, and a random-effects structure containing intercepts for individual participants and by-participant slopes for colour type. The GLMM revealed evidence for goal-dependent capture to target colours ($p < .001$). Distractors matching a target colour ($M = 84.21\%$, $SD = 6.83\%$) were significantly more likely to be fixated than distractors of non-target colour ($M = 56.88\%$, $SD = 6.83\%$). The goal-dependent contrast for shape type also had a significant effect on fixations ($p < .001$). However, there was also a significant interaction between the goal-dependent contrasts for colour type and shape type ($p < .001$). Two follow-up repeated-measures *t*-tests analysed the effect of the shape type goal-dependent contrast at each level of the colour type goal-dependent contrast, using Bonferroni-corrected significance levels of .025. For distractors that did *not* share their colour with a target, those of target shape were not fixated significantly more often than those of non-target shape ($t(35) = 1.64$, $p = .110$). In contrast, for distractors that *did* share their colour with a target, those that also shared their shape with a target ($M = 86.14\%$, $SD = 4.08\%$) were fixated significantly more often than those of non-target shape ($M = 82.31\%$, $SD = 4.08\%$; $t(35) = 3.98$, $p < .001$). Overall, although the target shapes seem to have played a role in guiding participants' attention, this role was contingent on the presence of target colour. As such, colour was found to be the target feature chiefly used for perceptual attentional guidance.

Supplementary Table 7.4. Chapter 2 (Experiment 1)

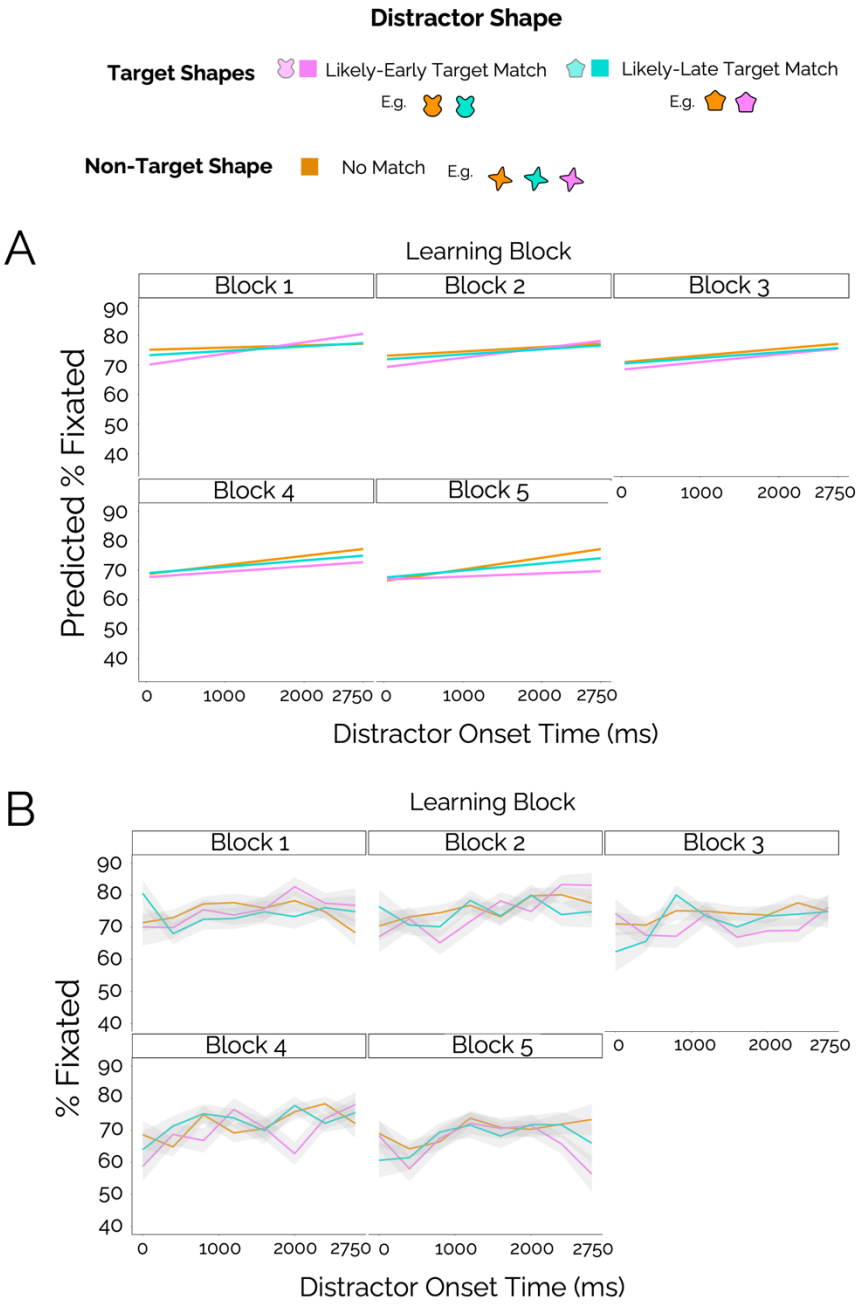
Experiment 1 Optimal GLMM Fixed Effects Output for *Preliminary* Analysis of Effects of Colour Type and Shape Type on Distractor Fixation Likelihood

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No *Colour* Match vs. Target *Colour* Match)	**-1.02**	**0.05**	**-21.06**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target *Colour* Match)	**-0.21**	**0.10**	**-2.14**	**.032**
Goal-dependent Contrast (No *Shape* Match vs. Target *Shape* Match)	**-0.16**	**0.02**	**-6.97**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target *Shape* Match)	0.01	0.05	0.12	.908
Goal-dependent Contrast (No *Colour* Match vs. Target *Colour* Match) : Goal-dependent Contrast (No *Shape* Match vs. Target *Shape* Match)	**0.11**	**0.03**	**3.89**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target *Colour* Match) : Goal-dependent Contrast (No *Shape* Match vs. Target *Shape* Match)	-0.01	0.07	-0.02	.983

Note. This fixed-effect model matrix was rank deficient (as the factors of Colour Type and Shape Type were not completely crossed for distractors) so not all interaction terms are given. This did not however hinder my investigations into whether target colour and/or shape seemed to be guiding attention.



Supplementary Figure 7.3. Chapter 2 (Experiment 1). (A) Visualisation of the fixed effects output of the GLMM for Experiment 1 giving the predicted percentage of distractors fixated during target absent trials across levels of colour type, onset times, and all learning blocks. **(B)** The actual recorded percentage of distractors fixated across levels of colour type, onset times, and all learning blocks in Experiment 1. This plot only includes data from target absent trials. Here and in subsequent plots, he solid pink, blue, and orange lines represent the mean values, while the grey shaded areas represent ±1 *SE* around the mean. For the plot only, data were smoothed by rounding onset times to the nearest 400 ms.



Supplementary Figure 7.4. Chapter 2 (Experiment 1). (A) Visualisation of the fixed effects output of the additional GLMM for Experiment 1 giving the predicted percentage of distractors fixated during target absent trials between levels of *shape* type, onset times, and all learning blocks. The optimal GLMM had a random-effects structure containing intercepts for individual participants and by-participant slopes for shape type and block number. The full output of this GLMM is given below in Supplementary Table 7.5. Of primary interest, the GLMM revealed that the prediction contrast of the shape type variable did not have a significant effect on distractor fixations overall (p = .166), nor did it interact significantly with onset time (p = .506), with block number (p = .181), or with onset time and block number together (p = .132). In other words, there were no significant differences between

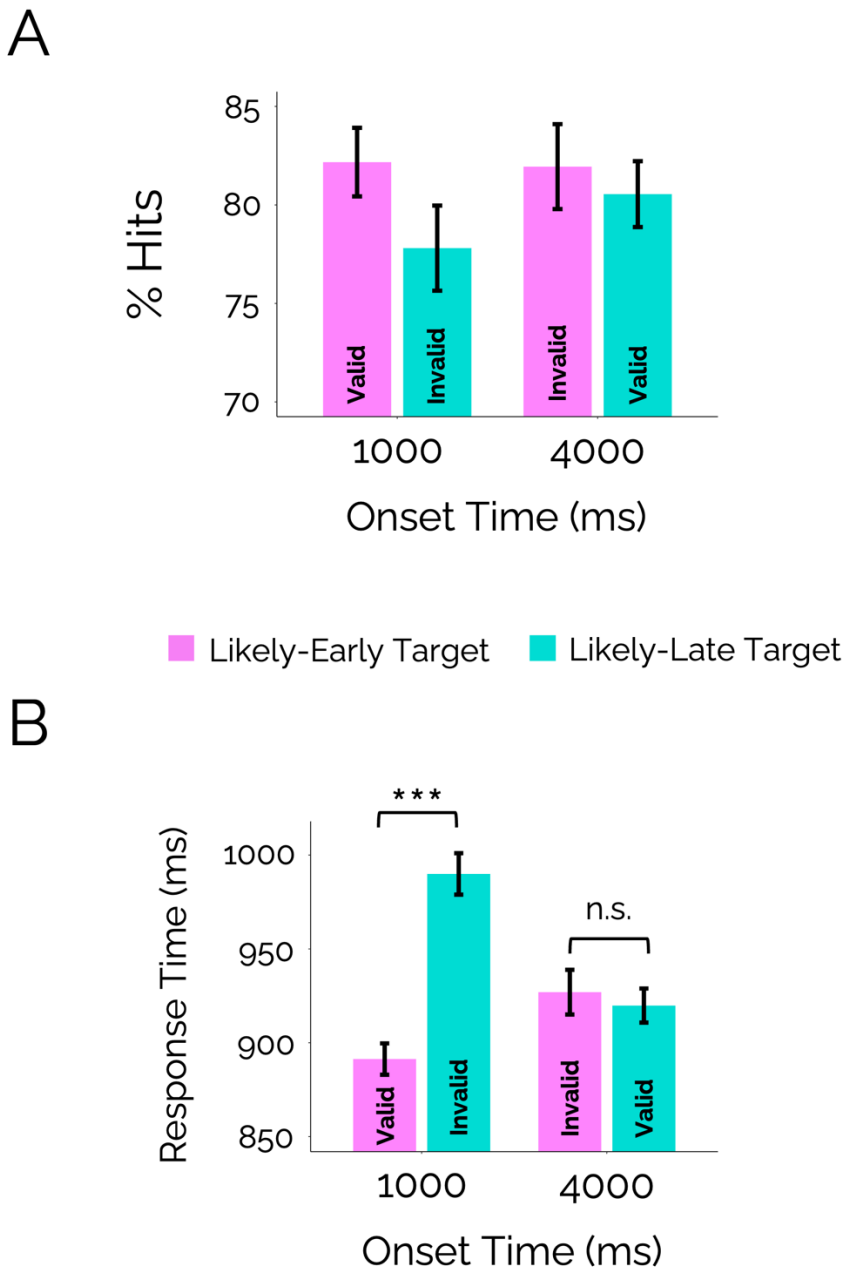
participants' likelihoods to fixate distractors of likely-early target shape and likely-late target shape, even when onset time and block number were considered. The GLMM therefore provided no evidence for temporal tuning of shape-based attentional guidance in line with the regularities in target timing. **(B)** The actual recorded percentage of distractors fixated for different levels of shape type, onset times, and all learning blocks in Experiment 1. This plot only includes data from target absent trials. For the plot only, data were smoothed by rounding onset times to the nearest 400 ms.

Supplementary Table 7.5. Chapter 2 (Experiment 1)

Experiment 1 Optimal GLMM Fixed Effects Output for Distractor Fixation Likelihood, Shape Type

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No Shape Match vs. Target Shape Match)	0.05	0.03	1.63	.103
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match)	0.05	0.04	1.39	.166
Onset Time	**0.09**	**0.01**	**6.51**	**< .001**
Block Number	**-0.10**	**0.03**	**-3.82**	**< .001**
Goal-dependent Contrast (No Shape Match vs. Target Shape Match) : Onset Time	0.01	0.02	0.15	.882
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match) : Onset Time	-0.02	0.04	-0.66	.506
Goal-dependent Contrast (No Shape Match vs. Target Shape Match) : Block Number	0.02	0.02	1.06	.289
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match) : Block Number	0.05	0.04	1.34	.181
Onset Time : Block Number	0.01	0.01	0.19	.851

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No Shape Match vs. Target Shape Match) : Onset Time : Block Number	**0.04**	**0.02**	**2.19**	**.029**
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match) : Onset Time : Block Number	0.06	0.04	1.51	.132



Supplementary Figure 7.5. Chapter 2 (Experiment 2). (A) Mean (untransformed) percentage hits for identifying targets in the testing block in Experiment 2, for likely-early and likely-late targets appearing at each onset time. Error bars represent ±1 standard error (*SE*) around the mean. A 2x2 ANOVA analysing the effects of target likelihood and onset time on hits (with hits having undergone a square transformation in line with *boxcox* recommendations) revealed that neither factor, nor their interaction, significantly affected hits. The full output of this ANOVA is shown in Supplementary Table 7.6 below. **(B)** Mean response times (RTs) for identifying targets in the testing block, for likely-early and likely-late targets appearing at each onset time. A 2x2 (target likelihood x onset time) ANOVA (on untransformed RT values in line with *boxcox* recommendations) revealed a significant main effect of target likelihood on RTs ($p < .001$). Overall, participants were significantly faster to identify the likely-

early target (M = 897 ms, SD = 49 ms) than the likely-late target (M = 950 ms, SD = 49 ms). The ANOVA also revealed a significant interaction between target likelihood and onset time ($p < .001$). A follow-up t-test revealed that, when targets appeared at 1000 ms, target likelihood significantly affected RTs ($t(47) = -6.98$, $p < .001$, $d = -1.01$, $BF_{10} > 1000$) whereby the likely-early target (M = 891 ms, SD = 69 ms) was identified significantly faster than the likely-late target (M = 990 ms, SD = 69 ms). A second follow-up t-test revealed that, when targets appeared at 4000 ms, target likelihood had no significant effect on RTs ($t(47) = 0.45$, $p = .652$, $d = 0.07$, $BF_{10} = 0.17$). The statistical significance of these follow-up comparisons is indicated in the figure with asterisks: *** = $p < .001$, n.s. = not significant. Full output of the ANOVA analysing RTs is shown in Supplementary Table 7.7 below.

Supplementary Table 7.6. Chapter 2 (Experiment 2)

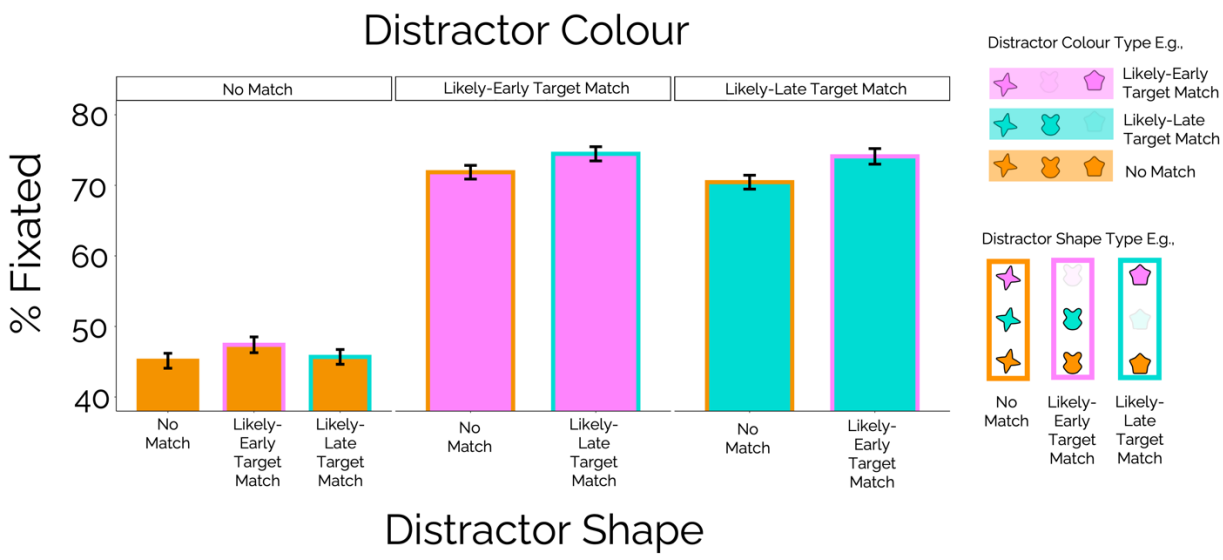
Hits ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	0.74	1	47	.393	.003
Target Likelihood	1.54	1	47	.220	.011
Onset Time : Target Likelihood	0.14	1	47	.709	.001

Supplementary Table 7.7. Chapter 2 (Experiment 2)

RT ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	3.37	1	47	.073	.009
Target Likelihood	**17.50**	**1**	**47**	**< .001**	**.063**
Onset Time : Target Likelihood	**26.77**	**1**	**47**	**< .001**	**.082**



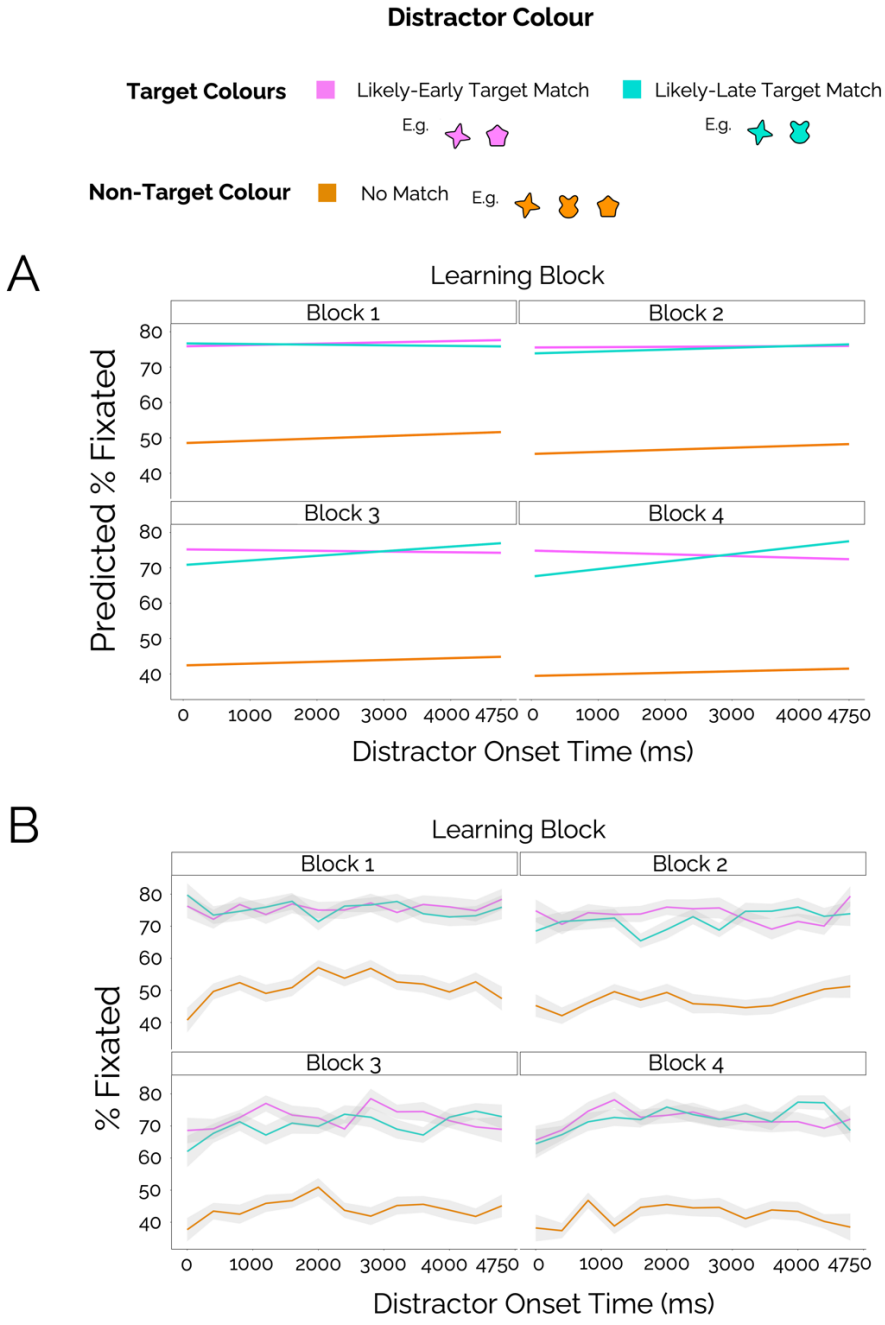
Supplementary Figure 7.6. Chapter 2 (Experiment 2). Mean percentage of distractors fixated across levels of colour type and shape type, for distractors from target-absent learning session trials in Experiment 2. Example distractors for each level of colour type and shape type for the example likely-early and likely-late targets are shown on the right. To investigate if participants used either target colour and/or target shape to guide their attention, a preliminary GLMM analysis investigated the overall effects of colour type and shape type, and their interaction, on fixation likelihood. Here, I focussed on effects of the goal-dependent contrasts, with the full optimal GLMM output given in Supplementary Table 7.8. The optimal GLMM had a fixed-effects structure containing colour type, shape type, and their interaction, and a random-effects structure containing intercepts for individual participants and by-participant slopes for colour type and shape type. The GLMM revealed evidence for goal-dependent capture to target colours ($p < .001$). Distractors matching a target colour (M = 72.72%, SD = 7.53%) were significantly more likely to be fixated than distractors of non-target colour (M = 46.09%, SD = 7.53%). The goal-dependent contrast for shape type also had a significant effect on fixations ($p < .001$). However, inconsistent with goal-dependent capture to target shapes, participants overall fixated more distractors of non-target shape (M = 62.50%, SD = 2.78%) than of target shape (M = 60.42%, SD = 2.78%). Interestingly, as for Experiment 1, there was a significant interaction between the goal-dependent contrasts for colour type and shape type ($p = .001$). Two follow-up repeated-measures t-tests analysed the effect of the shape type goal-dependent contrast at each level of the colour type goal-dependent contrast, using Bonferroni-corrected significance levels of .025. For distractors that did *not* share their colour with a target, those of target shape were not fixated significantly more often than those of non-target shape ($t(47) = 1.91$, $p = .063$). In contrast, for distractors that *did* share their colour with a target, those that also shared their shape with a target (M = 74.27%, SD = 3.19%) were fixated significantly more often than those of non-target shape (M = 71.17%, SD = 3.19%; $t(47) = 4.76$, $p < .001$). Overall, although the target shapes seem to have played a role in guiding participants' attention, this role was contingent on the presence of target colour. As such, as for Experiment 1, colour was found to be the target feature chiefly used for perceptual attentional guidance.

Supplementary Table 7.8. Chapter 2 (Experiment 2)

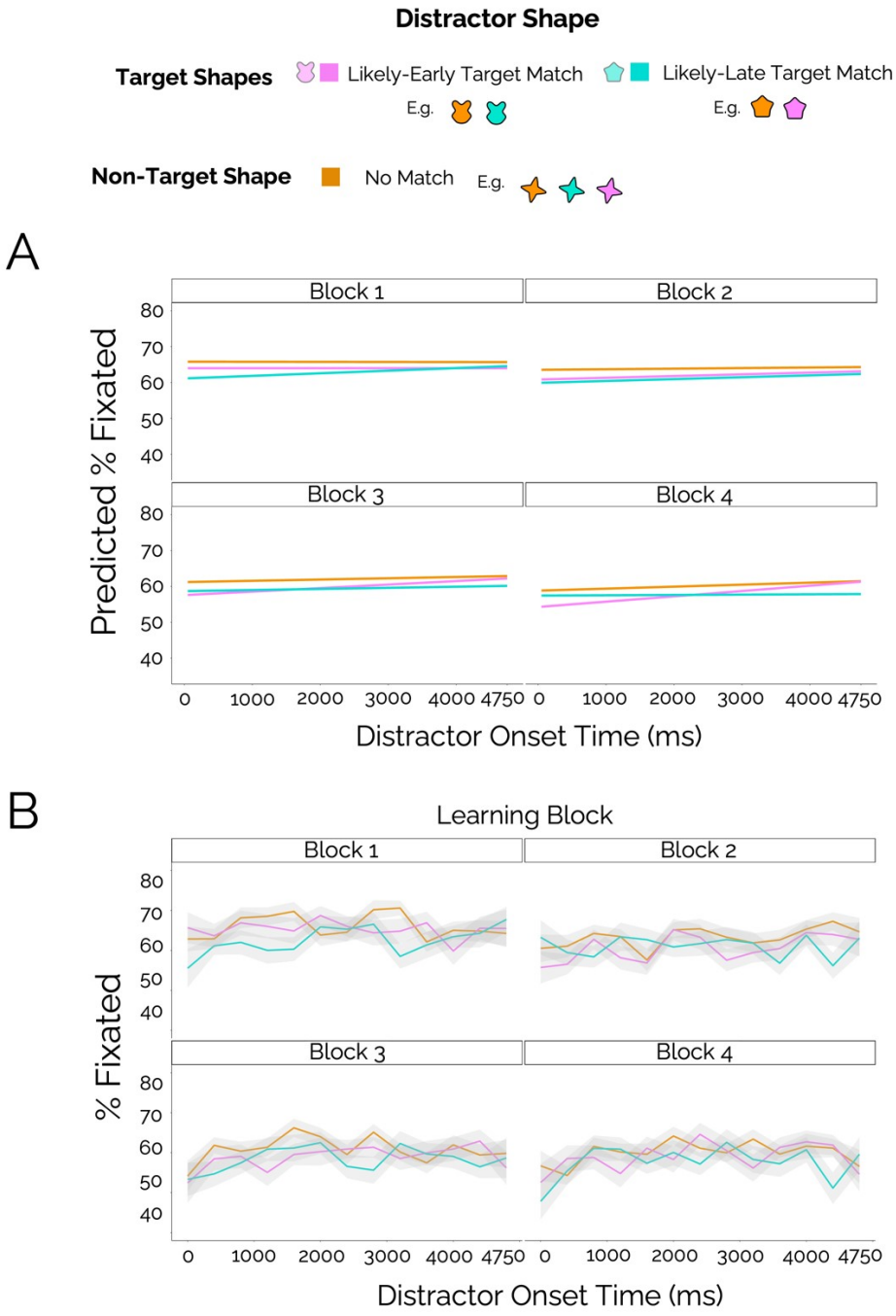
Experiment 2 Optimal GLMM Fixed Effects Output for *Preliminary* Analysis of Effects of Colour Type and Shape Type on Distractor Fixation Likelihood

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No *Colour* Match vs. Target *Colour* Match)	**-0.87**	**0.05**	**-17.62**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target *Colour* Match)	-0.07	0.07	-0.98	.328
Goal-dependent Contrast (No *Shape* Match vs. Target *Shape* Match)	**-0.10**	**0.02**	**-4.65**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target *Shape* Match)	- 0.07	0.04	-1.82	.069
Goal-dependent Contrast (No *Colour* Match vs. Target *Colour* Match) : Goal-dependent Contrast (No *Shape* Match vs. Target *Shape* Match)	**0.06**	**0.02**	**3.20**	**.001**
Prediction Contrast (Likely-Early vs. Likely-Late Target *Colour* Match) : Goal-dependent Contrast (No *Shape* Match vs. Target *Shape* Match)	0.01	0.04	0.21	.834

Note. This fixed-effect model matrix was rank deficient (as the factors of Colour Type and Shape Type were not completely crossed for distractors) so not all interaction terms are given. This did not however hinder my investigations into whether target colour and/or shape seemed to be guiding attention. Here, and in subsequent supplementary tables, significant predictors are shown in bold.



Supplementary Figure 7.7. Chapter 2 (Experiment 2). (A) Visualisation of the fixed effects output of the GLMM for Experiment 2 giving the predicted percentage of distractors fixated during target absent trials across levels of colour type, onset times, and all learning blocks. **(B)** The actual recorded percentage of distractors fixated across levels of colour type, onset times, and all learning blocks in Experiment 2. This plot only includes data from target absent trials. The solid pink, blue, and orange lines represent the mean values, while the grey shaded areas represent ±1 *SE* around the mean. For this plot, data were smoothed by rounding onset times to the nearest 400 ms.



Supplementary Figure 7.8. Chapter 2 (Experiment 2). (A) Visualisation of the fixed effects output of the additional GLMM for Experiment 2 giving the predicted percentage of distractors fixated during target absent trials across levels of *shape* type, onset times, and all learning blocks. The optimal GLMM had a random-effects structure containing intercepts for individual participants and by-participant slopes for shape type and block number. The full output of this GLMM is given below in Supplementary Table 7.9. Of primary interest, the GLMM revealed that the prediction contrast of the shape type variable did not have a significant effect on distractor fixations overall (p = .362), nor did it interact significantly with onset time (p = .466), with block number (p = .554), or with onset time

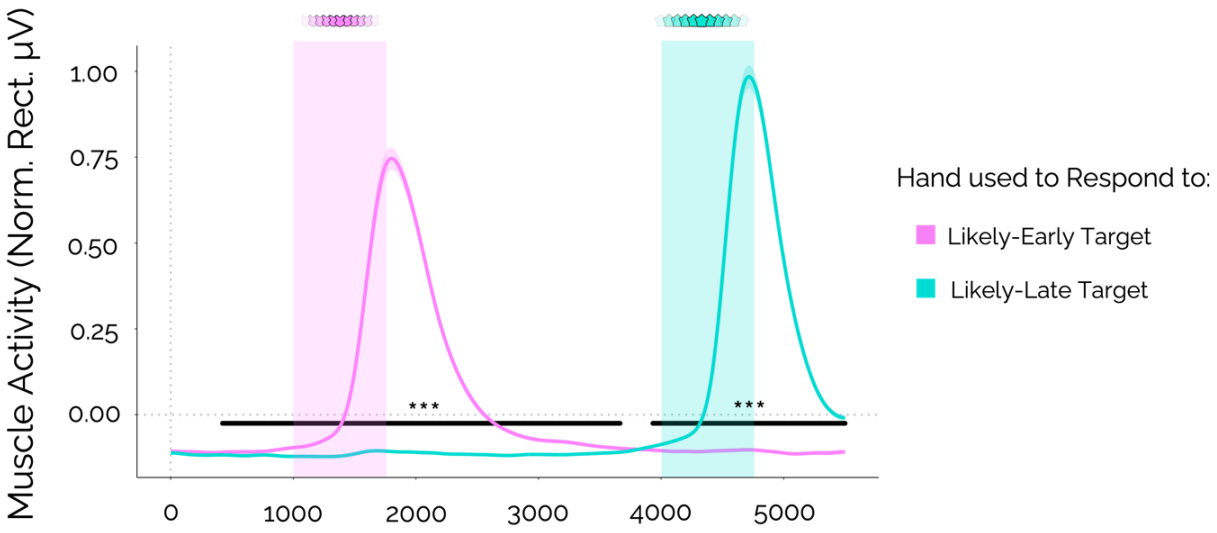
and block number together (p = .068). In other words, there were no significant differences between participants' likelihoods to fixate distractors of likely-early target shape and likely-late target shape, even when onset time and block number were considered. The GLMM therefore provided no evidence for temporal tuning of shape-based attentional guidance in line with the regularities in target timing. **(B)** The actual recorded percentage of distractors fixated across levels of shape type, onset times, and all learning blocks in Experiment 2. This plot only includes data from target absent trials. For the plot only, data were smoothed by rounding onset times to the nearest 400 ms.

Supplementary Table 7.9. Chapter 2 (Experiment 2)

Experiment 2 Optimal GLMM Fixed Effects Output for Distractor Fixation Likelihood, Shape Type

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No Shape Match vs. Target Shape Match)	**0.07**	**0.02**	**3.83**	**< .001**
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match)	- 0.03	0.03	-0.91	.362
Onset Time	**0.03**	**< 0.01**	**2.83**	**.005**
Block Number	**-0.09**	**0.02**	**-3.75**	**< .001**
Goal-dependent Contrast (No Shape Match vs. Target Shape Match) : Onset Time	-0.01	0.01	-0.93	.352
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match) : Onset Time	-0.02	0.02	-0.73	.466
Goal-dependent Contrast (No Shape Match vs. Target Shape Match) : Block Number	0.01	0.01	-0.04	.971
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match) : Block Number	0.01	0.03	0.59	.554
Onset Time : Block Number	0.01	< 0.01	1.03	.304

Predictor	β	*SE*	*z*	*p*
Goal-dependent Contrast (No Shape Match vs. Target Shape Match) : Onset Time : Block Number	0.01	0.01	0.20	.841
Prediction Contrast (Likely-Early vs. Likely-Late Target Shape Match) : Onset Time : Block Number	-0.05	0.02	-1.83	.068



Supplementary Figure 7.9. Chapter 2 (Experiment 2). Normalised rectified muscle activity in hands used to respond to the likely-early and likely-late targets over the 5500 ms duration trials where both targets appeared, across all learning blocks in Experiment 2, recorded using EMG. The solid pink and blue lines represent the mean values and the shaded areas around them represent ±1 *SE*. The pink and blue columns indicate the time windows over which the likely-early and likely-late targets, respectively, appeared. The two black horizontal lines mark clusters of significant differences in activity between the two hands, where *** = $p < .001$. For the earlier cluster, the peak difference occurred at 1804 ms. For the later cluster, the peak difference occurred at 4717 ms.

7.2 Supplementary Materials for Chapter 3



Supplementary Figure 7.10. Chapter 3. Mean (untransformed) percentage hits for identifying targets in the learning session, separately for participants in each of the N, FT, MT, and FMT conditions. A mixed 4 x 2 x 5 ANOVA (see in Supplementary Table 7.10 for the full output) analysed the effects of condition, onset time, and block number on hits (with hits having undergone a square transformation in line with *boxcox* recommendations). Hits significantly depended on onset time ($p < .001$), with

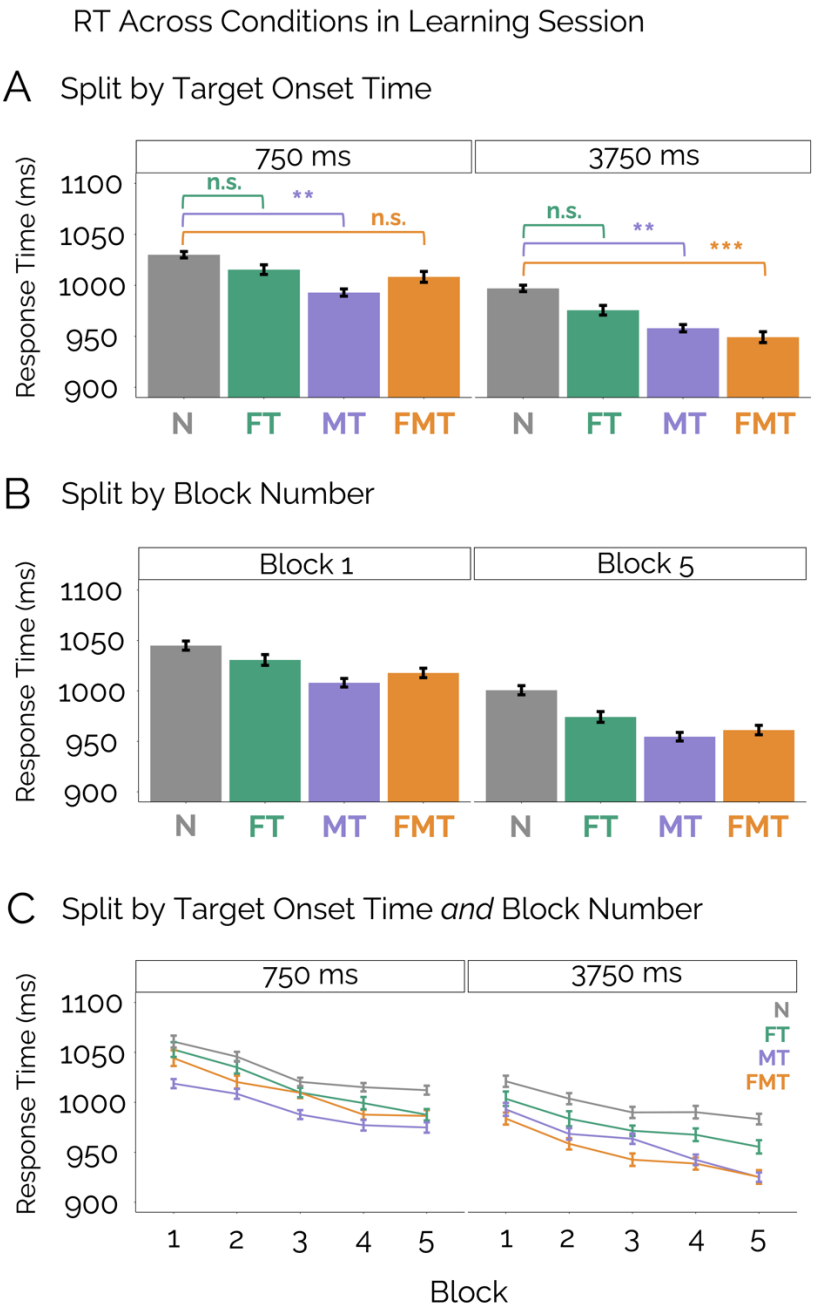
participants identifying significantly more late targets (3750 ms; M = 91.34%, SD = 4.18%) than early targets (750 ms; M = 89.46 %, SD = 4.18%). Block number also significantly affected hits (p < .001, Greenhouse-Geisser correction). Participants identified significantly more targets in the final learning block (M = 92.72%, SD = 5.93%) than in the first (M = 86.70%, SD = 5.93%; $t(255) = -11.95$, p < .001, d = -0.72, BF_{10} > 1000). Overall, condition did not significantly affect hits (p = .564). However, condition did interact significantly with onset (p = .031). Follow-up Welch's t-tests revealed that, when targets onset early, hits did not differ significantly from the N condition in either the FT condition ($t(121.84) = -0.10$, p = .921, d < 0.01, BF_{10} = 0.19), the MT condition ($t(124.89) = -0.78$, p = .439, d = -0.14, BF_{10} = 0.25), or the FMT condition ($t(125.45) = 0.47$, p = .640, d = 0.09, BF_{10} = 0.21). Again, when targets that onset late, hits in neither the FT condition ($t(124.30) = -1.74$, p = .084, d = -0.30), nor the MT condition ($t(123.76) = -1.89$, p = .061, d = -0.33), differed significantly from hits in the N condition. In contrast, hits for late targets were significantly higher in the FMT condition (M = 92.14%, SD = 5.13%) than the N condition (M = 89.81%, SD = 5.99%; $t(123.76) = -2.42$, p = .017, d = -0.42). However, the Bayes' Factors for all follow-up comparisons regarding late onset targets indicated only anecdotal evidence in favor of either the null (FT: BF_{10} = 0.74; MT: BF_{10} = 0.95) or alternative hypothesis (FMT: BF_{10} = 2.59) in each case. The statistical significance of these follow-up comparisons is indicated in part A of the figure with asterisks: * = p < .05, n.s. = not significant.

Supplementary Table 7.10. Chapter 3

Learning Session Hits Full Mixed ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Condition	0.68	3	252	.564	.004	NA
Onset	**28.24**	**1**	**252**	**< .001**	**.013**	**NA**
Block Number	**54.72**	**3.48[1]**	**877.77[1]**	**< .001[1]**	**.057**	**0.87**
Condition : Onset	**3.00**	**3**	**252**	**.031**	**.004**	**NA**
Condition : Block Number	1.73	10.45[1]	877.77[1]	.067[1]	.006	0.87
Onset : Block Number	0.60	3.85[1]	969.72[1]	.656[1]	< .001	0.96
Condition : Onset : Block Number	0.59	11.54[1]	969.72[1]	.842[1]	.001	0.96

Note. Significant predictors are shown in bold. [1]Greenhouse-Geisser correction applied due to significant sphericity violation as indicated by a Mauchly's Test of Sphericity.



Supplementary Figure 7.11. Chapter 3. Mean (untransformed) response times (RTs) for identifying targets in the learning session, for participants in each of the N, FT, MT, and FMT conditions. A mixed 4 x 2 x 5 ANOVA (see Supplementary Table 7.11 for the full output) analysed the effects of condition, onset time, and block number on RT (with RTs having undergone a reciprocal square root transformation in line with *boxcox* recommendations). The ANOVA revealed RT depended significantly on target onset time ($p < .001$). Overall, targets were identified faster when they onset late (M = 970 ms, SD = 35 ms), than when they onset early (M = 1012 ms, SD = 35 ms). Block number also significantly affected RT ($p < .001$, Greenhouse-Geisser correction), with targets in the final learning block identified faster (M = 973 ms, SD = 38 ms) than targets in the first learning block (M = 1025 ms, SD = 38 ms; $t(255) = -16.29$, $p < .001$, $d = 0.99$, $BF_{10} > 1000$). Overall, RT was also significantly

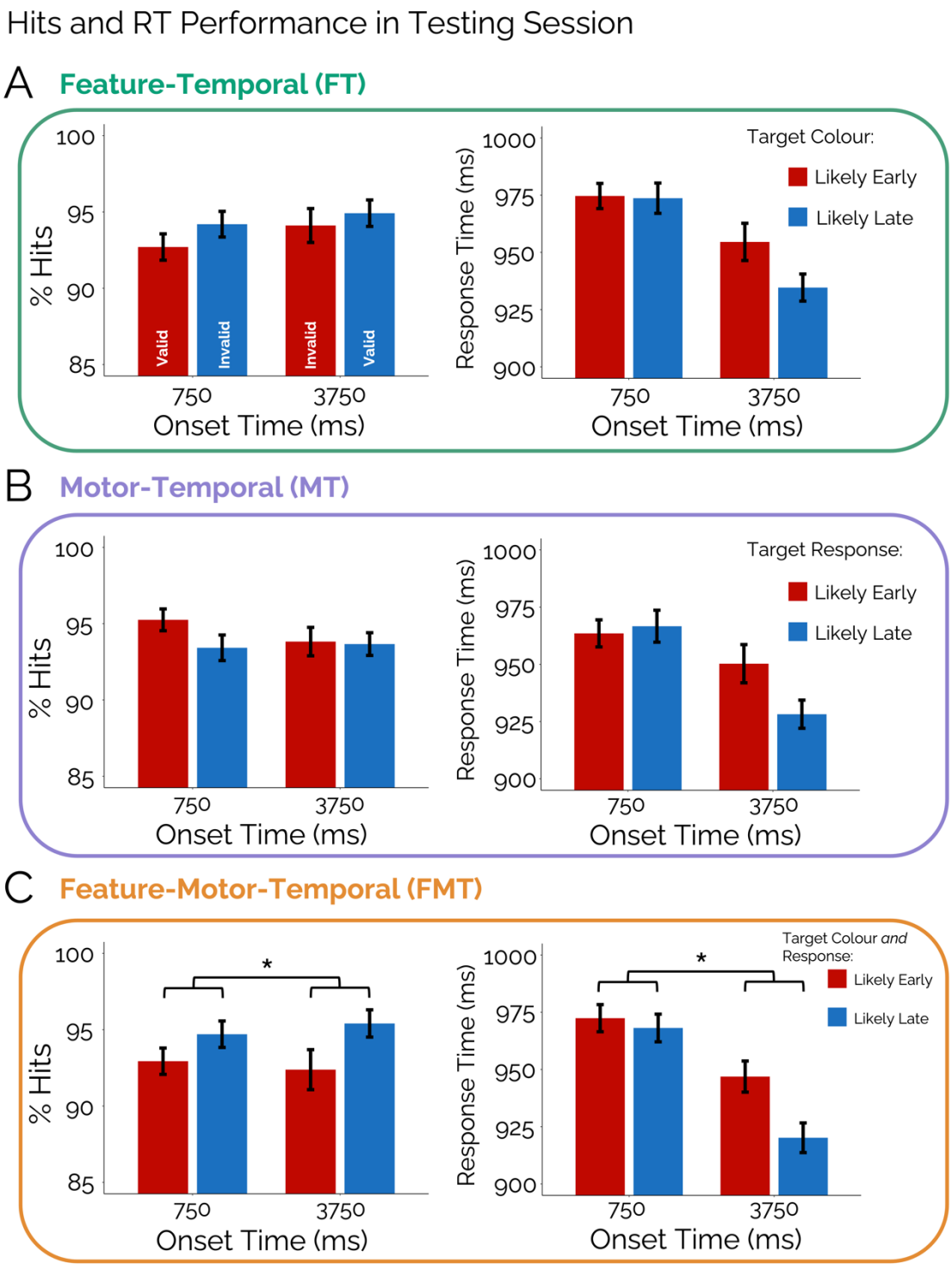
affected by which regularity condition participants were assigned to (p = .026). The effect of condition interacted significantly with onset time (p = .006). Welch's t-tests following up this significant interaction revealed that, when targets onset early, MT was the only condition for which RTs differed significantly from the N condition (t(125.67) = -2.65, p = .009, d = 0.47, BF_{10} = 4.39). MT participants (M = 993 ms, SD = 74 ms) identified early onset targets significantly faster than N participants (M = 1031 ms, SD = 85 ms). Early-target RTs in both the FT (t(123.03) = -1.02, p = .310, d = 0.15, BF_{10} = 0.30) and FMT (t(124.72) = -1.47, p = .145, d = 0.25) conditions did not differ significantly from the N condition, though evidence for the latter null effect was only anecdotal (FMT: BF_{10} = 0.50). When targets onset late, RTs again did not differ significantly between the FT and N conditions (t(123.12) = -1.53, p = .129, d = 0.25), though evidence for the null hypothesis was only anecdotal (BF_{10} = 0.54). In contrast, participants in the MT condition (M = 958 ms, SD = 71 ms) were significantly faster to identify late targets than participants in the N condition (M = 998 ms, SD = 82 ms; t(125.67) = -2.91, p = .004, d = 0.51, BF_{10} = 8.17). Participants in the FMT condition (M = 950 ms, SD = 76 ms) were also significantly faster to identify late targets than N participants (t(125.73) = -3.47, p < .001, d = 0.61, BF_{10} = 37.84). The statistical significance of these follow-up comparisons is indicated in part A of the figure with asterisks: ** = p < .01, *** = p < .001, n.s. = not significant. An additional exploratory t-test compared RTs for late targets between MT and FMT conditions, as both conditions demonstrated significant benefits compared to N, though no significant difference was found (t(124.82) = -0.71, p = .477, d = 0.12, BF_{10} = 0.24).

Supplementary Table 7.11. Chapter 3

Learning Session RTs Full Mixed ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Condition	**3.13**	**3**	**252**	**.026**	**.028**	**NA**
Onset	**192.97**	**1**	**252**	**< .001**	**.053**	**NA**
Block Number	**115.68**	**3.33[1]**	**840.41[1]**	**< .001[1]**	**.044**	**0.83**
Condition : Onset	**4.20**	**3**	**252**	**.006**	**.004**	**NA**
Condition : Block Number	0.82	10.00[1]	840.41[1]	.610[1]	< .001	0.83
Onset : Block Number	2.23	4	1008	.064	< .001	NA
Condition : Onset : Block Number	1.71	12	1008	.060	.001	NA

Note. [1]Greenhouse-Geisser correction applied due to significant sphericity violation as indicated by a Mauchly's Test of Sphericity.



Supplementary Figure 7.12. Chapter 3. Mean (untransformed) percentage hits (left side) and RTs (right side) for identifying targets in the testing block, for likely-early and likely-late targets appearing at each onset time. For each of the FT, MT, and FMT conditions separately, 2 x 2 repeated-measures ANOVAs analysed the effects of onset time and target likelihood on hits and RT. Hits and RT values were transformed prior to analysis in line with *boxcox* recommendations. **(A)** For the FT condition,

hits underwent a square transformation prior to analysis. The ANOVA (see Supplementary Table 7.12) revealed that neither onset (p = .117), target likelihood (p = .340), nor their interaction (p = .571) significantly affected hits. RT values underwent a log transformation prior to analysis. The ANOVA (see Supplementary Table 7.13) revealed that onset time significantly affected RT (p < .001), with late onset targets (M = 940 ms, SD = 38 ms) identified significantly faster than early onset targets (M = 974 ms, SD = 38 ms). Neither target likelihood (p = .173), nor the interaction between likelihood and onset (p = .074) was significant. **(B)** For the MT condition, the ANOVA analysing hits (which underwent a square transformation) revealed the effects of onset time (p = .549), target likelihood (p = .207), and their interaction (p = .393), were not significant (see Supplementary Table 7.14). RTs underwent a reciprocal transformation prior to analysis. The RT ANOVA (see Supplementary Table 7.15) revealed that late onset targets (M = 935 ms, SD = 36 ms) were again identified significantly faster than early onset targets (M = 964 ms, SD = 36 ms; p < .001). Neither target likelihood (p = .232), nor the interaction between onset and likelihood (p = .107) significantly affected RT. **(C)** For the FMT condition, hits were squared transformed prior to analysis (see Supplementary Table 7.17 for full ANOVA output). Unlike the other two conditions, target likelihood significantly affected hits (p = .030). Overall, likely-late targets were identified significantly more often (M = 95.13%, SD = 5.28%) than likely-early targets (M = 92.78%, SD = 5.28%), indicated in the figure with * = p < .05. Onset time (p = .699) and the interaction between onset time and likelihood (p = .695) did not significantly affect hits. RTs underwent a square root transformation prior to analysis. The ANOVA (see Supplementary Table 7.17) revealed that target likelihood also significantly affected RTs (p = .040), with likely-late targets overall identified faster (M = 941 ms, SD = 41 ms) than likely-early targets (M = 966 ms, SD = 41 ms), also indicated in the figure. Onset time also significantly affected RT (p < .001), with late onset targets (M = 928 ms, SD = 36 ms) identified faster than early onset targets (M = 971 ms, SD = 36 ms). The interaction between onset and likelihood was not significant (p = .069).

Supplementary Table 7.12. Chapter 3.

FT Testing Session Hits Full Repeated-Measures ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	2.52	1	63	.117	.006
Target Likelihood	0.93	1	63	.340	.005
Onset Time : Target Likelihood	0.32	1	63	.571	< .001

Supplementary Table 7.13. Chapter 3.

FT Testing Session RT Full Repeated-Measures ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	**19.31**	**1**	**63**	**< .001**	**.023**
Target Likelihood	1.90	1	63	.173	.002
Onset Time : Target Likelihood	3.29	1	63	.074	.002

Note. Significant predictors are shown in bold.

Supplementary Table 7.14. Chapter 3.

MT Testing Session Hits Full Repeated-Measures ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	0.36	1	63	.549	.001
Target Likelihood	1.63	1	63	.207	.005
Onset Time : Target Likelihood	0.74	1	63	.393	.003

Supplementary Table 7.15. Chapter 3.

MT Testing Session RT Full Repeated-Measures ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	**15.75**	**1**	**63**	**< .001**	**.026**
Target Likelihood	1.45	1	63	.232	.003
Onset Time : Target Likelihood	2.68	1	63	.107	.004

Supplementary Table 7.16. Chapter 3.

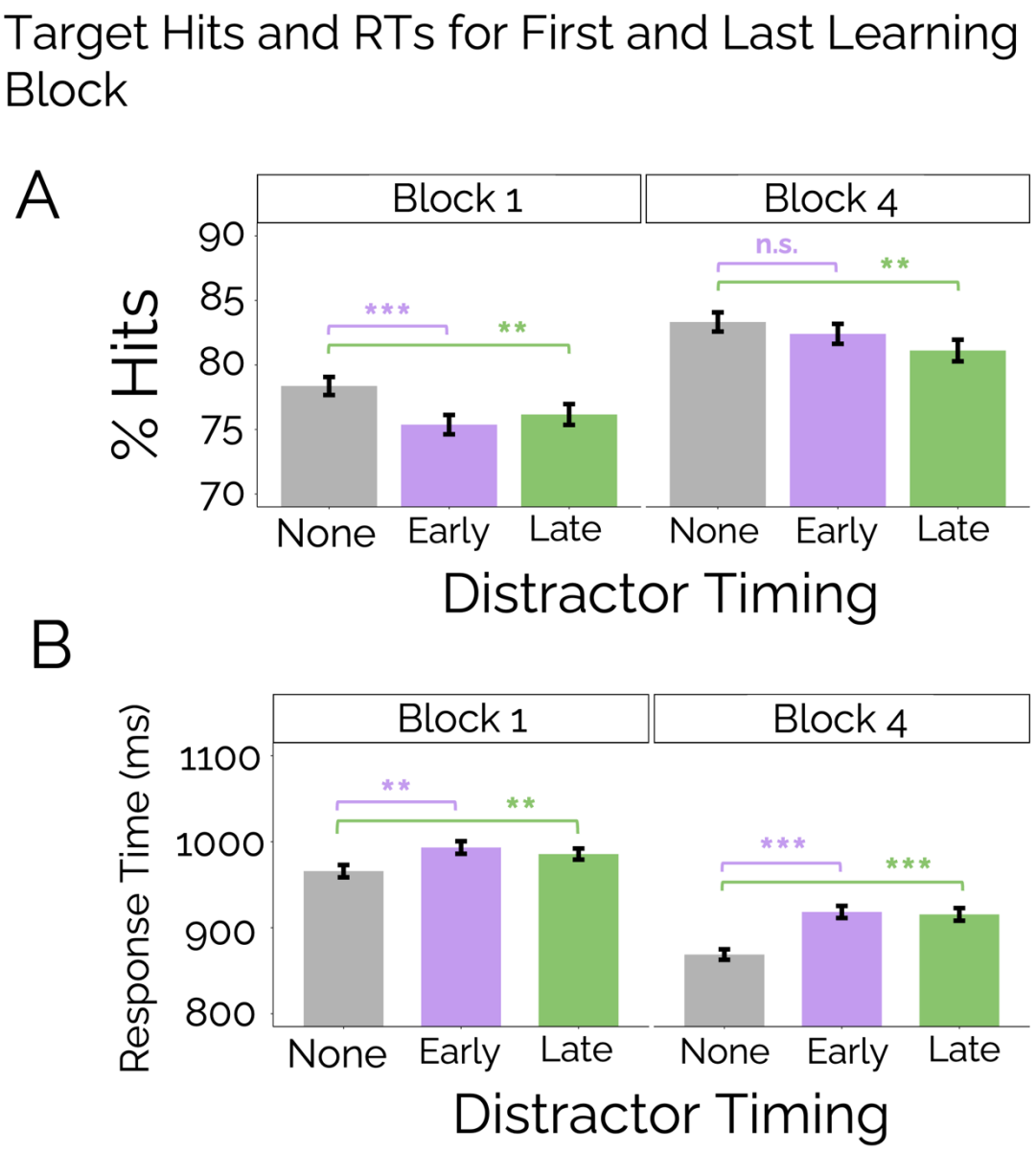
FMT Testing Session Hits Full Repeated-Measures ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	0.15	1	63	.699	< .001
Target Likelihood	**4.93**	**1**	**63**	**.030**	**.021**
Onset Time : Target Likelihood	0.16	1	63	.695	< .001

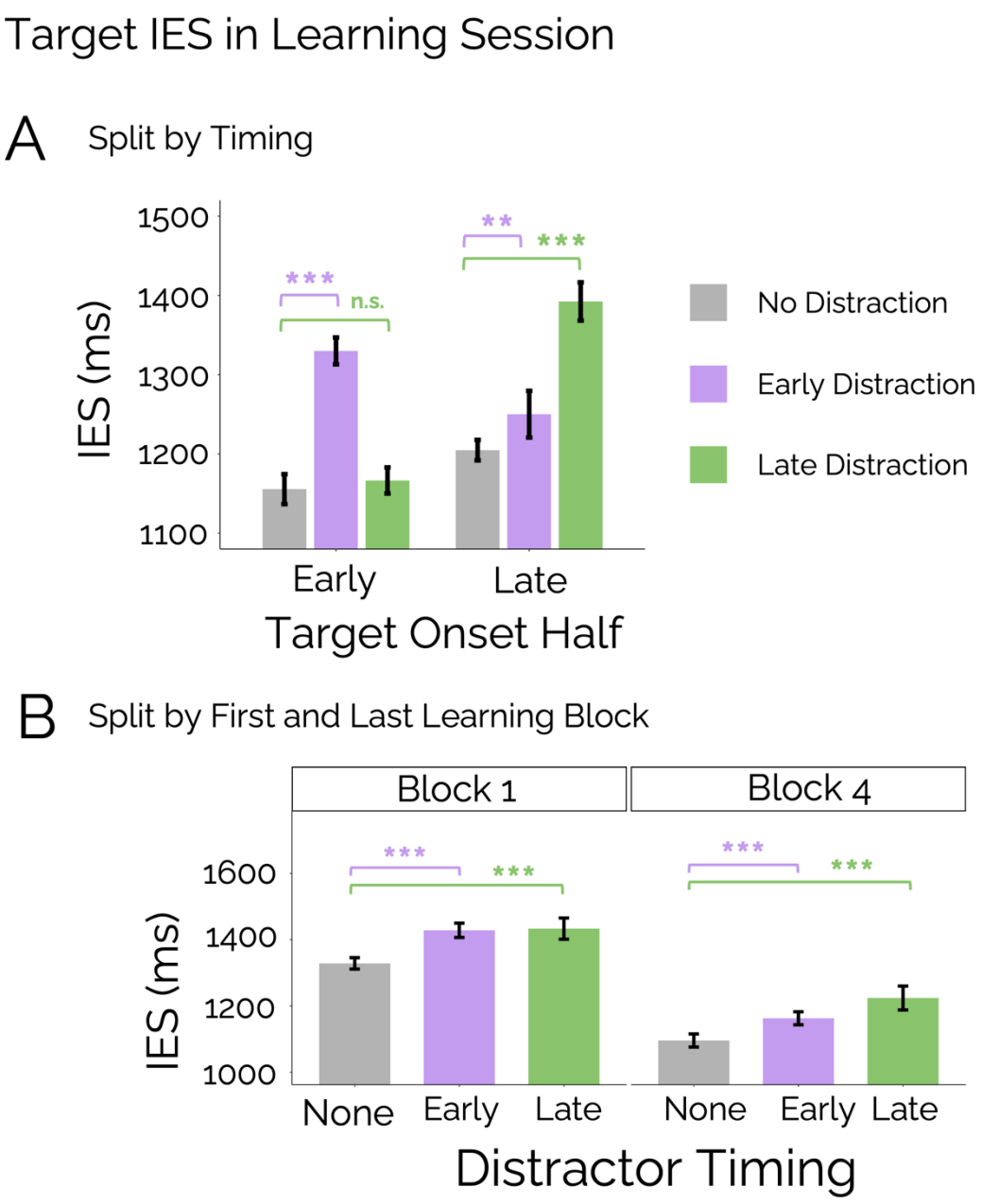
Supplementary Table 7.17. Chapter 3.

FMT Testing Session RT Full Repeated-Measures ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G
Onset Time	**43.31**	**1**	**63**	**< .001**	**.040**
Target Likelihood	**4.40**	**1**	**63**	**.040**	**.007**
Onset Time : Target Likelihood	3.43	1	63	.069	.004



Supplementary Figure 7.13. Chapter 4. Mean percentage hits **(A)** and RTs **(B)** for targets in trials with no distraction (grey bars), early distraction (purple bars), and late distraction (green bars), for the first and final learning blocks separately. The error bars represent ±1 *SE* around the mean. Distractor timing and block number interacted significantly for both hits and RT. The results of follow-up comparisons between targets in trials with early or late distraction and targets in trials with no distraction are described in full in the results (Basic Effects of Distraction on Performance Over Time) and their statistical significance is indicated in the figure with asterisks: *** = $p < .001$, ** = $p < .01$, n.s. = not significant.



Supplementary Figure 7.14. Chapter 4. Mean (untransformed) IES scores for identifying targets in learning session trials with early distraction (purple), late distraction (green), and no distraction (grey), split by early and late onset time **(A)**, and first and final learning block **(B)**. A repeated-measures ANOVA was run (see Supplementary Table 7.18 for the full output) on reciprocally-transformed IES values. Block number significantly affected IES (p < .001, Greenhouse-Geisser correction), with targets identified more efficiently in the last learning block (M_{IES} = 1161 ms, SD_{IES} = 241 ms) than the first (M_{IES} = 1397 ms, SD_{IES} = 241 ms; $t(79)$ = -9.16, p < .001, d = -0.69, BF_{10} > 1000). IES also significantly depended on distractor timing (p < .001, Greenhouse-Geisser correction). Compared to targets in trials with no distraction (M_{IES} = 1080 ms, SD_{IES} = 93 ms), targets were identified less efficiently in trials with early distraction (M_{IES} = 1290 ms, SD_{IES} = 104 ms; $t(79)$ = -10.83,

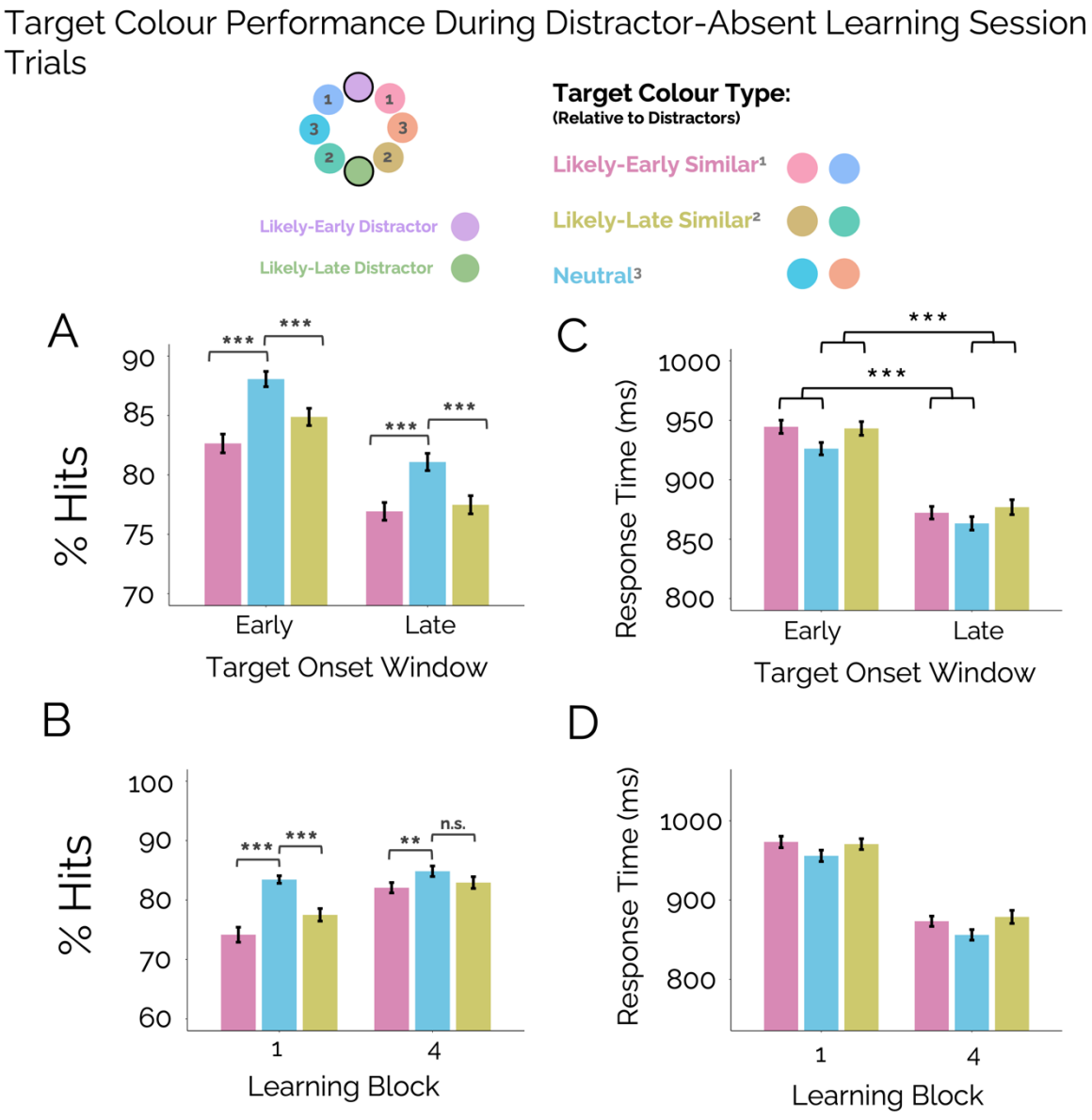
$p < .001$, $d = -0.80$, $BF_{10} > 1000$), or late distraction ($M_{IES} = 1279$ ms, $SD_{IES} = 102$ ms; $t(79) = -9.54$, $p < .001$, $d = -0.73$, $BF_{10} > 1000$). Distractor timing interacted significantly with target onset window ($p < .001$, Greenhouse-Geisser correction). For early targets alone, distractor timing significantly affected IES ($p < .001$, Greenhouse-Geisser correction). Early targets in trials with early distraction ($M_{IES} = 1330$ ms, $SD_{IES} = 102$ ms) were identified significantly less efficiently than early targets in trials with no distraction ($M_{IES} = 1156$ ms, $SD_{IES} = 78$ ms; $t(79) = -14.92$, $p < .001$, $d = -1.30$, $BF_{10} > 1000$). As expected, there was no difference between early targets in trials with no distraction and with late distraction ($M_{IES} = 1166$ ms, $SD_{IES} = 77$ ms; $t(79) = -0.83$, $p = .410$, $d = -0.11$, $BF_{10} = 0.17$). For late targets alone, distractor timing again significantly affected IES ($p < .001$, Greenhouse-Geisser correction). Late targets in trials with early distraction ($M_{IES} = 1250$ ms, $SD_{IES} = 193$ ms) were identified significantly less efficiently than late targets in trials with no distraction ($M_{IES} = 1205$ ms, $SD_{IES} = 129$ ms; $t(79) = -3.09$, $p = .003$, $d = -0.21$, $BF_{10} = 9.73$), as were late targets in trials with late distraction ($M_{IES} = 1392$ ms, $SD_{IES} = 197$ ms; $t(79) = -10.47$, $p < .001$, $d = -0.85$, $BF_{10} > 1000$). Returning to the main ANOVA output, distractor timing also interacted significantly with block number ($p = 0.40$, Greenhouse-Geisser correction). For targets in the first learning block, distractor timing significantly affected IES ($p < .001$, Greenhouse-Geisser correction). Compared to Block 1 targets in trials with no distraction, ($M_{IES} = 1328$ ms, $SD_{IES} = 143$ ms), those in trials with early distraction ($M_{IES} = 1428$ ms, $SD_{IES} = 178$ ms; $t(79) = -5.92$, $p < .001$, $d = -0.53$, $BF_{10} > 1000$), or late distraction ($M_{IES} = 1433$ ms, $SD_{IES} = 224$ ms; $t(79) = -4.97$, $p < .001$, $d = -0.39$, $BF_{10} > 1000$), were identified significantly less efficiently. For targets in the final learning block, distractor timing still significantly affected IES ($p < .001$). Compared to Block 4 targets in trials with no distraction, ($M_{IES} = 1096$ ms, $SD_{IES} = 124$), those in trials with early distraction ($M_{IES} = 1163$ ms, $SD_{IES} = 178$ ms; $t(79) = -5.45$, $p < .001$, $d = -0.38$, $BF_{10} > 1000$), or late distraction ($M_{IES} = 1224$ ms, $SD_{IES} = 218$ ms; $t(79) = -7.07$, $p < .001$, $d = -0.51$, $BF_{10} > 1000$), were again identified significantly less efficiently. The statistical significance of all follow-up comparisons is indicated in the figure with asterisks: *** = $p < .001$, ** = $p < .01$, n.s. = not significant.

Supplementary Table 7.18. Chapter 4

Learning Session: Effects of Distraction on Target IES Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	0.52	1	79	.474	< .001	NA
Distractor Timing	**82.93**	**1.82[1]**	**143.89[1]**	**< .001[1]**	**.015**	**0.91**
Block Number	**51.31**	**2.29[1]**	**180.97[1]**	**< .001[1]**	**.039**	**0.76**
Target Onset Window : Distractor Timing	**146.10**	**1.58[1]**	**124.81[1]**	**< .001[1]**	**.027**	**0.79**
Target Onset Window : Block Number	0.10	3	237	.963	< .001	NA
Distractor Timing : Block Number	**2.31**	**5.26[1]**	**415.39[1]**	**.040[1]**	**< .001**	**0.88**
Target Onset Window : Distractor Timing : Block Number	1.48	4.86[1]	384.10[1]	.196[1]	< .001	0.81

Note. Significant predictors are shown in bold. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.



Supplementary Figure 7.15. Chapter 4. Mean (untransformed) percentage hits **(A, B)** and RTs **(C, D)** for targets in distractor-absent learning session trials that appeared either in a colour similar to the likely-early distractor colour (pink bars), in a colour similar to the likely-late distractor colour (gold bar), or in a colour between the two distractor colours (blue bars). Performance is split by target onset window **(A, C)** and, separately, by the first and final learning blocks **(B, D)**. Repeated-measures ANOVAs were run on square-transformed hits and square root-transformed RTs, separately, with full outputs provided in Supplementary Table 7.19 and Supplementary Table 7.20,respectively. Here, I focus on main effects and interactions involving the *colour type* variable, as the primary variable of interest. **Hits.** Colour type significantly affected target hits ($p < .001$). Follow-up comparisons revealed that targets similar in colour to the likely-early (M = 79.82%, SD = 4.81%; $t(79) = -7.00$, $p < .001$, $d = -0.80$, $BF_{10} > 1000$) or likely-late (M = 81.26%, SD = 5.03%; $t(79) = -4.60$, $p < .001$, $d = -0.37$, $BF_{10} > 1000$) distractors were hit significantly less overall than targets in *'neutral'* colours between the two distractor colours (M = 84.63%, SD = 4.11%). Colour type interacted significantly with target onset

window (p = .038). A follow-up comparison revealed that, for early targets alone, colour type significantly affected hits (p < .001). When targets onset early, those in a similar colour to likely-early distractors (M = 82.64%, SD = 5.55%; t(79) = -6.68, p < .001, d = -0.75, BF_{10} > 1000), and those in a similar colour to likely-late distractors (M = 84.88%, SD = 5.29%; t(79) = -4.20, p < .001, d = -0.47, BF_{10} = 282), were hit significantly less than neutral targets (M = 88.06%, SD = 4.74%). For late targets alone, colour type also significantly affected hits (p < .001). When targets onset late, those in a similar colour to the likely-early distractors (M = 76.93%, SD = 5.54%; t(79) = -5.04, p < .001, d = -0.58, BF_{10} > 1000), and those in a similar colour to the likely-late distractors (M = 77.48%, SD = 5.95%; t(79) = -3.98, p < .001, d = -0.46, BF_{10} = 133), were again hit significantly less than the neutral targets (M = 81.08%, SD = 5.02%). Returning to the main ANOVA output, colour type also interacted significantly with block number (p < .001). For targets in the first learning block, colour type significantly affected hits (p < .001). Block 1 targets in a similar colour to the likely-early distractors (M = 74.17%, SD = 8.77%; t(79) = -7.40, p < .001, d = -0.82, BF_{10} > 1000), and those in a similar colour to the likely-late distractors (M = 77.51%, SD = 7.76%; t(79) = -5.55, p < .001, d = -0.61, BF_{10} > 1000), were hit significantly less than neutral targets (M = 83.45%, SD = 7.10%). For targets in the last learning block, colour type again significantly affected hits (p = .038). Block 4 targets in a similar colour to the likely-early distractors (M = 82.08%, SD = 6.07%) were still hit significantly less than the neutral targets (M = 84.85%, SD = 6.66%; t(79) = -2.68, p = .009, d = -0.31, BF_{10} = 3.46). In contrast, hits in Block 4 did not differ significantly between targets in a similar colour to the likely-late distractors (M = 82.94%, SD = 6.80%) and neutral targets (t(79) = -1.50, p = .138, d = -0.19, BF_{10} = 0.36). The statistical significance of all follow-up comparisons is indicated in the figure with asterisks: *** = p < .001, ** = p < .01, n.s. = not significant. The three-way interaction between colour type, target onset window, and block number was not significant (p = .404). **RT.** Colour type also significantly affected target RTs (p < .001, Greenhouse-Geisser correction). Follow-up comparisons (illustrated in C) revealed that, overall, RTs were significantly slower for taps on targets in a similar colour to the likely-early (M = 913 ms, SD = 25 ms; t(79) = 3.79, p < .001, d = 0.43, BF_{10} = 75.00), or likely-late (M = 914 ms, SD = 26 ms; t(79) = 3.99, p < .001, d = 0.44, BF_{10} = 138) distractors, compared to targets in a neutral colour (M = 899 ms, SD = 23 ms). For RT, neither the two-way interaction between colour type and target onset window (p = .335), the two-way interaction between colour type and block number (p = .670, Greenhouse-Geisser correction), nor the three-way interaction between colour type, target onset window, and block number was significant (p = .892).

Supplementary Table 7.19. Chapter 4

Learning Session: Distractor-Similar vs. Neutral Colour for Target Hits Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	**70.39**	**1**	**79**	**< .001**	**.036**	**NA**
Colour Type	**21.99**	**2**	**158**	**< .001**	**.014**	**NA**
Block Number	**16.68**	**2.42[1]**	**191.28[1]**	**< .001[1]**	**.018**	**0.81**
Target Onset Window : Colour Type	**3.34**	**2**	**158**	**.038**	**< .001**	**NA**
Target Onset Window : Block Number	0.41	3	237	.989	< .001	NA
Colour Type : Block Number	**4.88**	**6**	**474**	**<.001**	**.004**	**NA**
Target Onset Window : Colour Type : Block Number	1.03	6	474	.404	< .001	NA

Note. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.

Supplementary Table 7.20. Chapter 4

Learning Session: Distractor-Similar vs. Neutral Colour for Target RT Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	**68.67**	**1**	**79**	**< .001**	**.048**	**NA**
Colour Type	**10.67**	**1.85[1]**	**146.39[1]**	**< .001[1]**	**.002**	**0.93**
Block Number	**39.09**	**3**	**237**	**< .001**	**.045**	**NA**
Target Onset Window : Colour Type	1.10	2	158	.335	< .001	NA
Target Onset Window : Block Number	1.90	2.57[1]	203.03[1]	.139[1]	.001	0.86
Colour Type : Block Number	0.63	4.87[1]	384.97[1]	.670[1]	<.001	0.81
Target Onset Window : Colour Type : Block Number	0.38	6	474	.892	< .001	NA

Note. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.



Supplementary Figure 7.16. Chapter 4. Mean IES for targets that appeared early or late in the trial, and in a colour similar to either the likely-early (pink bars) or likely-late (gold bars) distractor colour. A repeated-measures ANOVA was run on reciprocally-transformed IES values for targets in distractor-absent learning session trials that appeared in a colour similar to one of the distractor colours (i.e., not neutrally-coloured targets). The full ANOVA output is provided in Supplementary Table 7.21. I focus on main effects and interactions involving the *colour type* variable. Overall, colour type did not significantly affect IES (p = .237). Further, the two-way interaction between colour type and block number (p = .155), and the three-way interaction between colour type, target onset window, and block number (p = .164), were both non-significant. Of interest, the two-way interaction between colour type and target onset window was significant (p = .024). Follow-up comparisons revealed that, when targets appeared early during trials, those similar to the likely-early distractor colour (M_{IES} = 1230 ms, SD_{IES} = 147 ms) were collected significantly *less* efficiently than those similar to the likely-late distractor colour (M_{IES} = 1188 ms, SD_{IES} = 147 ms; $t(79) = 2.33$, p = .023, d = 0.20, BF_{10} = 1.56). By contrast, when targets appeared late, there was no significant difference in IES between these colour types ($t(79) = 0.17$, p = .863, d = 0.03, BF_{10} = 0.13). The significance of the follow-up comparisons is indicated in the figure with asterisks: * = p < .05 and n.s. = not significant.

Supplementary Table 7.21. Chapter 4

Learning Session: Likely-Early vs. Likely-Late Distractor-Similar Colour for Target IES Full ANOVA Output

Predictor	*F*	df_1	df_2	*p*	η^2_G	ε
Target Onset Window	0.37	1	79	.543	< .001	NA
Colour Type	1.42	1	79	.237	< .001	NA
Block Number	**41.18**	**2.53[1]**	**200.17[1]**	**< .001[1]**	**.046**	**0.84**
Target Onset Window : Colour Type	**5.34**	**1**	**79**	**.024**	**< .001**	**NA**
Target Onset Window : Block Number	1.30	3	237	.275	< .001	NA
Colour Type : Block Number	1.76	3	237	.155	<.001	NA
Target Onset Window : Colour Type : Block Number	1.72	3	237	.164	< .001	NA

Note. [1]Greenhouse-Geisser correction applied due to a significant violation of sphericity, as indicated by Mauchly's Test of Sphericity.