Liverpool Hope University

School of Psychology

An Exploration of the Effects of Low Target Prevalence on Attention to Subsequent Visual Events

A thesis submitted in accordance with the requirements of Liverpool Hope University

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By

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ABSTRACT

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Georgina Bailey

The thesis investigates how target prevalence in a primary visual task affects attentional engagement in a temporally proximate secondary task through behavioural and electrophysiological studies. Research shows that low prevalence targets are routinely missed across professional domains from medical screening to airport security. While the Low Prevalence Effect (LPE) is well-documented within individual tasks, how prevalence-induced expectations influence sequential tasks remains unclear. Four behavioural experiments employed a sequential paradigm consisting of letter discrimination and dot-probe detection tasks. Target prevalence, distractor confusability, feedback, and dot-probe eccentricity were manipulated to examine attentional resource distribution. Results demonstrated that low prevalence targets significantly impaired subsequent dot-probe performance through slower response times, decreased accuracy, reduced sensitivity, and more conservative response bias. Effects persisted despite the predictable dot-probe task, were partially moderated but not eliminated by feedback, and scaled linearly with prevalence imbalance. Interestingly, dot-probe eccentricity did not affect performance, suggesting effects were not due to spatial attention adjustments. A fifth experiment using electroencephalography (EEG) examined the neural underpinnings of these effects. Event-related potential (ERP) data revealed that low prevalence targets elicited larger P3a amplitudes, reflecting increased attentional capture, with P3a amplitude correlating with performance decrements. High prevalence targets elicited larger P3b amplitudes, indicating sustained working memory engagement. Early attentional processing (P1) predicted P3a responses for rare but not frequent targets, demonstrating a cascade of attentional modulation from early processing stages to subsequent orienting responses. Together these findings indicate that unexpected events temporarily capture attention through automatic mechanisms, depleting resources available for subsequent tasks. These results are consistent with attention-orienting mechanisms underlying expectancy violations, whereby prevalence imbalance affects sequential judgements through both automatic attentional capture and sustained working memory demands. Results have implications for professional visual search contexts where targets are rare but consequential, suggesting that prevalence-induced resource depletion may impact sequential judgements beyond the immediate task.

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List of Abbreviations

2AFC – Two Alternative Forced Choice

AB – Attentional Blink

ABC – Arousal-Biased Competition

ACC – Anterior Cingulate Cortex

ACT – Attentional Control Theory

ANOVA – Analysis of Variance

AOSPAN – Automated Operation Span

CCT – Cognitive Control Theory

CI – Confidence Interval

CMS – Common Mode Sense

CMT – Conflict Monitoring Theory

DRL – Driven Right Leg

EEG – Electroencephalography

EMF – Eye Movement Feedback

ERP – Event-Related Potential

ERN – Error-Related Negativity

FIR – Finite Impulse Response

fMRI – Functional Magnetic Resonance Imaging

FVF – Functional Viewing Field

GLME – Generalised Linear Mixed-Effect Models

HEOG – Horizontal Electrooculogram

ICA – Independent Component Analysis

IES – Inverse Efficiency Score

ISI – Inter Stimulus Interval

LBFTS – Look But Fail To See

LME – Linear Mixed-Effect Model

LPE – Low Prevalence Effect

MDM – Multiple Decision Model

Ne – Error-related negativity (alternative term for ERN)

PES – Post-Error Slowing

PICC – Prevalence-Induced Concept Change

PLT – Perceptual Load Theory

PRP – Psychological Refractory Period

ROC – Receiver Operating Characteristic

RSVP – Rapid Serial Visual Presentation

RT – Response Time

SD – Standard Deviation

SE – Standard Error

SDT – Signal Detection Theory

SOA – Stimulus Onset Asynchrony

SSM – Subsequent Search Misses

VEOG – Vertical Electrooculogram

WMC – Working Memory Capacity

Declaration of Authorship

I, *Georgina Bailey* declare that the thesis entitled *An Exploration of the Effects of Low Target Prevalence on Attention to Subsequent Visual Events* and the work presented in it is my own and has been generated from original research.

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To Tabby and Eames: you are twelve now. I started this journey over half your lifetime ago, and now here you are, immortalised in the 'book' I have written. Thank you for the fun, the stress, and everything in between. Most of all, thank you for just being you—don't forget to remember who you are. To Susan Sausage (aka Supervisor Sue), the most ginger and smooth-brained of all cats, thank you for the strokes, the purring, and for simply being.

And finally (D is for Diary), to you, Juey. Who needs boring anyway? I love you, and I always will, whatever life decides to throw at us.

Enjoy the thesis. And remember…

Don’t worry, don’t be afraid, ever, because this is just a ride.

- Bill Hicks

Chapter 1. Introduction

Visual search — the process of looking through a scene or display for a target item amongst non-target distractors — is a fundamental component of everyday human behaviour. We search for our keys on a cluttered desk, scan a crowd for a familiar face, or monitor a road scene for potential hazards. With respect to searching for targets, an important area of research has examined how the frequency, or prevalence, of targets being sought affects attentional and decision-making processes (Wolfe et al., 2005). Research has shown that rare targets are detected more slowly and missed more often than targets that appear more frequently, a phenomenon termed the Low Prevalence Effect (LPE; Wolfe et al., 2005).

The implications of target prevalence extend far beyond laboratory settings. In medical imaging (see Evans et al., 2013), radiologists must often examine multiple types of abnormalities within a single scan, with each type having different base rates of occurrence. For example, lung nodules appear in approximately 5% of chest X-rays, but pulmonary embolisms occur in less than 1% of cases yet both require accurate detection for optimal patient outcomes. In mammography, it is estimated that only 0.3% of inspected scans will contain a tumour (Gur et al., 2004), but it has been reported that radiologists miss as many as 30% of cancers (Berlin, 1994). Despite the critical nature of these tasks, even highly trained radiologists continue to overlook targets (Krupinski, 1996; Nodine et al., 1996; Nodine & Kundel, 1987), potentially resulting in serious consequences. It has been reported that between 24% and 36% of mammography target misses occur when radiologists do not search the area of the scan containing the lesion (Krupinski, 1996). Additionally, radiologists typically only examine approximately 50% of a scan before reaching a ‘target-absent’ conclusion and determining that there are no lesions present (Krupinski, 1996).

In security screening (see Wolfe et al., 2013), security operators must detect multiple categories of threats that vary in frequency. Common prohibited items might appear relatively frequently, whilst dangerous weapons or explosive devices are exceptionally rare, but pose severe security risks. In this case, searching for multiple threats is known to lead to poor detection of low prevalence threats (Donnelly et al., 2019).

The implications of the effects of prevalence in more complex visual tasks where more than one decision may need to be made are equally striking. For example, the ability of air traffic controllers to monitor the flightpaths of multiple aircraft may be impacted by visual signs of sudden and unexpected shifts in flight paths, or even changes in weather (Aricò et al., 2016). Similarly, lifeguards working on a beach might have their ability to monitor the safety of water users impacted by the appearance of sudden shifts in wave patterns, or even sharks (Fenner et al., 1999; Page et al., 2011). Additionally, prevalence effects can influence hazard detection when driving. For instance, a cyclist emerging from a side street or a deer running onto the road may impact the avoidance of another car (Kosovicheva et al., 2022).

In all these complex visual tasks, it is important to understand how we respond to rare targets whilst maintaining responsiveness to other events. Understanding how the LPE operates, and whether it extends to affect subsequent visual judgements, is the central concern of this thesis.

In the current thesis, my interest is in characterising the effects of target prevalence in one task on another that occurs soon afterwards. The fundamental question of interest is whether the effects of prevalence that we expect to see in the first task affect performance in a subsequent task? The idea underpinning the work in this thesis is that the prevalence of a target appearing in an initial task will impact attention and decision-making, thereby affecting performance in a subsequent task.

The question explored in the present thesis is not new in the sense that different aspects of the question have been explored previously. In the Introduction, I will outline this previous literature. To do this, I first review the evidence exploring how and why prevalence impacts behaviour through its influence on attentional guidance, the size of the attentional window, thresholds for search termination, and target identification. Second, I review evidence which explores how and why rare visual events lead to slowed and error-prone performance on subsequent trials through their impact on attentional resource allocation and response thresholds. Third, I review the neural correlates associated with the appearance of low prevalence targets. I conclude by outlining the studies presented in Chapters 2–4 and explain how they address key issues emerging from the literature review.

The Impact of Target Prevalence on Detection

With respect to the specific task of searching for target objects, a particular area of research has examined how attentional and decision-making processes are affected by the prevalence of targets being sought. Research examining the effects of target prevalence has developed along two distinct methodological approaches. The first strand stems from visual search studies where a single target is set amongst an array of distractors. In visual search studies, the prevalence of the target is contrasted across conditions. In some studies, the dependent variables are response time and target misses, whilst other studies include eye movement recording to explore additional measures such as target verification times and search paths. The second strand of research utilises visual search paradigms but requires participants to search for more than one target. In these studies, the relative prevalence of the targets is manipulated so that one target appears more frequently. These studies add to the visual search literature by enabling exploration of how relative prevalence influences the strategic priorities of participants when deciding how to approach a search task.

It is worth noting that these two methodological strands also represent two conceptually distinct types of prevalence manipulation. In single-target paradigms, prevalence refers to the overall rate at which the target appears across trials — termed overall prevalence. In dual-target paradigms, prevalence refers to the relative frequency of one target compared to another — termed relative prevalence. Importantly, in both setups, only one of the two possible target types can be present on any given trial, meaning that changes in the prevalence of one target necessarily alter the prevalence of the other. This distinction is relevant because the mechanisms driving prevalence effects may differ depending on whether they arise from overall target rarity or from within-task competition between targets of differing frequency.

Rare targets are detected more slowly and missed more often than targets that appear more frequently (Wolfe et al., 2005). Visual search studies have shown that when low prevalence targets are detected, they are verified more slowly (Rich et al., 2008; Schwark et al., 2013; Wolfe et al., 2005, 2007). Eye movement studies have shown that low prevalence targets are commonly fixated but not identified (Hout et al., 2015), and that search paths are truncated before full examination (Peltier & Becker, 2016). Relative prevalence studies have shown that low prevalence targets are detected more slowly and less accurately than high prevalence targets (Cheng & Rich, 2018; Menneer et al., 2009). Taken together, these empirical phenomena reveal the behavioural markers of the Low Prevalence Effect (LPE).

Early accounts of the LPE suggested that it was caused by impulsive motor responses (Fleck & Mitroff, 2007); however, Van Wert and colleagues (2009) observed that the effect persisted even when participants were able to correct their initial responses. Other accounts propose that the effect is driven by shifts in bias during decision-making, such as adopting more conservative response criteria or elevated quitting thresholds that lead to premature search termination (Hout et al., 2015; Wolfe et al., 2007). Importantly, even when target selection is controlled using Rapid Serial Visual Presentation (RSVP) paradigms which eliminate spatial search requirements, rare targets continue to be missed more frequently than common ones (Hout et al., 2015). This finding indicates that perceptual failures in target identification also contribute to the LPE. Wolfe et al. (2022) have captured this aspect of perceptual failure by describing them as Look But Fail To See (LBFTS) errors.

The LPE has been replicated in many studies of both active and passive visual search (e.g., Kunar et al., 2010; Rich et al., 2008; Wolfe et al., 2007; Wolfe & Van Wert, 2010). The LPE may be mitigated by practice (Clark et al., 2015) but this mitigation is context specific (Kunar et al., 2010). Various intervention strategies have been proposed to mitigate the LPE including: intermittent bursts of high prevalence trials (Papesh et al., 2018), independent double reading (Kunar et al., 2021), blind proficiency testing (Pierce & Cook, 2020), voluntary task-switching (2025), manipulating the physical effort required to indicate target presence or absence (Moher & Leber, 2025), enabling participants to make slower responses (Kunar et al., 2010), giving explicit warnings (Lau & Huang, 2010), reward schemes (Zhang et al., 2025), or the ability to work with a partner on the same task (Wolfe et al., 2007); although none of these have been shown to eliminate the LPE.

Research has demonstrated that irrespective of search complexity, the most frequent visual search mistakes involve either not visually fixating on targets or terminating searches prematurely before examining the complete search space, termed selection errors (Fleck & Mitroff, 2007; Ishibashi et al., 2012; Wolfe et al., 2005; Zenger & Fahle, 1997). Another category of errors occurs when individuals fixate on targets yet still conclude targets are absent, known as identification errors, which have been linked to changes in decision criteria.

Many visual search studies exhibit low prevalence errors predicted by the Multiple Decision Model (MDM; Wolfe & Van Wert, 2010). The MDM was developed to understand the mechanisms underlying prevalence effects through the distinct but interacting cognitive processes of selection errors and identification errors. This dual-stage account explains why prevalence effects persist even when eye movement studies confirm that targets were fixated, as fixation ensures selection but does not guarantee successful identification. Research examining the contribution of target repetition and target expectation has provided further insights into the emergence of prevalence effects, demonstrating that both the frequency of target encounters and the expectations they generate contribute to the magnitude of the effect (Godwin et al., 2016). The MDM suggests that target prevalence affects both decision stages but through different mechanisms. At the selection stage, low prevalence conditions lead to the adoption of more stringent criteria for directing attention towards potential targets. This conservative selection bias means that fewer locations are selected for more detailed examination, increasing the likelihood that targets will be overlooked entirely. Even when targets are successfully selected for further processing, the identification stage is also subject to prevalence-induced bias. In low prevalence conditions, individuals adopt more conservative identification criteria, requiring stronger evidence before concluding that a selected item is indeed a target (Figure 1.1).

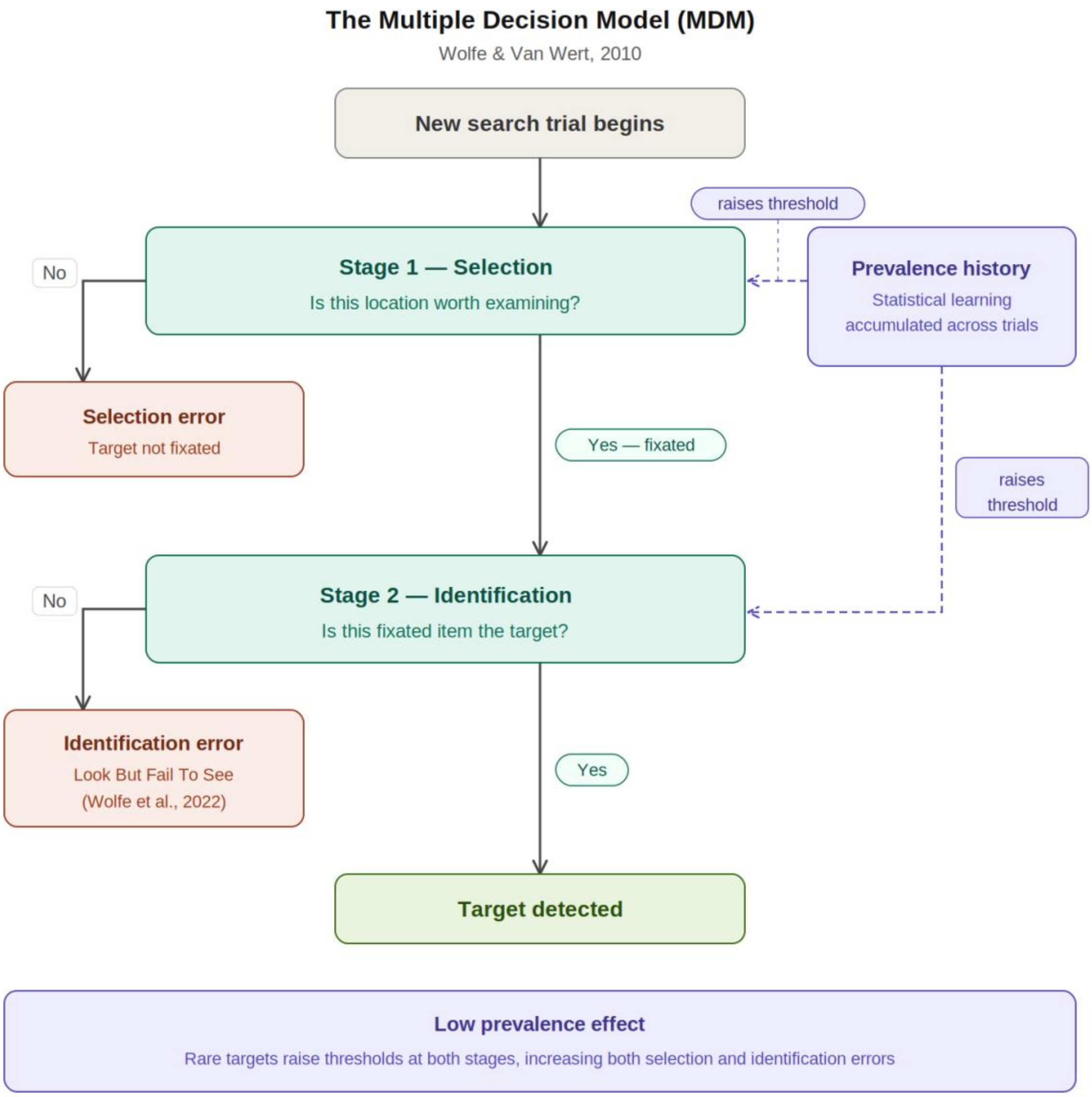


Figure 1.1. *Schematic of the Multiple Decision Model (MDM; Wolfe & Van Wert, 2010).* Prevalence history (dashed arrows) raises decision thresholds at both the selection and identification stages. Selection errors occur when a target location is never fixated. Identification errors (Look But Fail To See; Wolfe et al., 2022) occur when a fixated target is nonetheless classified as absent.

The MDM framework provides insights into why prevalence effects are so persistent and difficult to eliminate through training or instruction alone. The model suggests that both selection and identification processes are influenced by statistical learning mechanisms that operate largely outside conscious control. The inevitability of prevalence-induced biases has important implications for understanding how these effects might transfer to subsequent tasks, as the underlying mechanisms that drive prevalence effects within a single task may continue to operate and influence performance even when task requirements change.

Furthermore, the dual-stage nature of the MDM highlights the complexity of prevalence effects and suggests that interventions designed to mitigate these effects must address both selection and identification processes. Interventions that focus solely on improving target identification, for example, may be ineffective if they do not also address the selection biases that prevent targets from being adequately examined in the first place.

At this point, it is important to outline exactly what is meant by perceptual sensitivity and decision bias within the MDM framework. These terms should be thought of in the same way as they are within Signal Detection Theory (SDT; Green & Swets, 1966). When targets are rare, observers adopt more conservative decision criteria, requiring stronger evidence before responding ‘target present’. This conservative shift reflects an adaptation to the statistical structure of the environment, as false positive errors become increasingly costly when targets are infrequent. In addition, it is helpful to note that the idea of evidence accumulating to a perceptual or decisional threshold draws on the idea of evidence accumulation toward response boundaries, with prevalence effects emerging from changes in starting points, drift rates, or boundary separation. Under low prevalence conditions, the starting point for 'target absent' responses may be shifted closer to the decision boundary, reducing the amount of evidence required to terminate search (Wolfe et al., 2007). Alternatively, prevalence may affect the rate of evidence accumulation for target detection, with rare targets requiring more evidence to reach detection thresholds (Peltier & Becker, 2016). The application of SDT to prevalence effects reveals an important paradox: whilst the conservative shift in response criteria represents an optimal adaptation to the statistical environment in terms of minimising overall error rates, it comes at the cost of reduced sensitivity to rare but important targets.

So far, the evidence may appear to suggest that the LPE is unable to be mitigated by any intervention, being observed in different experimental paradigms in both novices and professionals (Evans et al., 2013; Wolfe et al., 2013). However, this is not the case. One study has challenged the view of prevalence effects as immutable. Zhang et al.'s (2023) study demonstrated that the low prevalence effect (LPE) manifested differently in experts versus novices. Medical practitioners were asked to detect hip fractures in 50 X-ray images with either high prevalence (80%, with 40 images containing fractures) or low prevalence (20%, with 10 images containing fractures). Results showed that experts exhibited the typical LPE, becoming more conservative in responding 'fracture-present' when prevalence was low. However, novices showed a reversed pattern, becoming more liberal and more likely to indicate 'fracture-present' in the low prevalence condition. This reversal suggests that expertise moderates how prevalence affects decision criteria in medical image interpretation. The authors propose that novices and experts may hold different beliefs about optimal diagnostic strategies. They suggested that the observed reversal of the LPE in novices was because of novices responding with greater caution, believing that a miss would result in a larger cost than a false positive. Although it is hard to understand why the belief in the cost of missing a hip fracture should only occur in the low prevalence condition, the finding provides some evidence that beliefs about risk may impact the LPE. It is important to note that this study has yet to be replicated, and given the surprising nature of these findings, they should be interpreted with appropriate caution.

Additionally, there is evidence of individual differences influencing the magnitude of the LPE. Schwark et al. (2013) explored the impact of working memory capacity (WMC) on the LPE. In their study, participants performed a visual search task at either 50% (high prevalence) or 4% (low prevalence) identifying whether a target letter X was present in an array of 100 random letters. They observed that participants with a higher WMC, as indexed by the automated operation span task (AOSPAN; Unsworth et al., 2005), showed reduced prevalence effects compared to those with a lower WMC. They suggested that these findings were due to participants with a higher WMC being better able to maintain task goals and resist the influence of statistical regularities.

Peltier and Becker's (2017) study utilised a battery of tests to explore whether factors including vigilance and personality type affected the magnitude of the LPE. In their task, participants performed a low prevalence visual search task (10% target prevalence) requiring them to detect a rotated T amongst an array of 24 items. They observed that higher visual working memory capacity (vWMC), better performance in a high prevalence visual search task, higher vigilance levels and higher levels of extroversion were predictors of better performance under low prevalence conditions.

Muhl-Richardson et al. (2018) used a dynamic search task where participants searched for the onset of a target colour in arrays of squares with colours that changed over time. In one experiment (Experiment 3), they measured WMC and tolerance of uncertainty (a measure known to be affected by trait anxiety). The results showed that the ability to detect the onset of low prevalence targets was affected by an interaction between WMC and intolerance of uncertainty.

It can be seen therefore, that the relationship between WMC and other factors appears to be important in understanding variations in the magnitude of the LPE. The most likely account of this relationship is that the capacity of executive attention (as reflected in WMC) influences vigilance and cognitive control considering the statistical regularities determined by the stimulus conditions. Whether or not this account is accurate, although the LPE appears to be a robust phenomenon, it does seem to be subject to individual differences.

The studies discussed above reveal that the LPE reflects a dynamic interaction between statistical learning and cognitive control mechanisms, rather than a fixed perceptual bias. Importantly, factors that modulate the magnitude of the LPE in single tasks - working memory capacity, vigilance, and response strategies, may also influence how prevalence effects transfer between tasks. If the LPE reflects capacity-limited attentional processes, then it would follow that individuals with greater cognitive resources might show reduced sequential transfer effects. Alternatively, if the LPE reflects statistical learning mechanisms, then individual differences might affect the rate of prevalence encoding but not the magnitude of sequential effects.

The LPE has also been shown to be affected by age. Goodhew and Edwards' (2024) study measured processing speed (operationalised as response times (RT) on high prevalence trials) and quitting thresholds (operationalised as RT on target absent trials) to predict the magnitude of the LPE. Their task required participants to detect guns in an array of photorealistic images at both low and high prevalence. They found that older adults had slower processing speeds and higher quitting thresholds than younger adults because they prioritised accuracy over speed in their responses. The result of this shift in strategy for older versus younger participants was a reduction in the LPE, indicating that age is a modulating factor for the LPE.

Finally, the LPE has been found to be affected by feedback. Schwark et al.'s (2012) study investigated whether false feedback could reduce the low prevalence effect in a visual search task. Participants searched for the letter 'X' among arrays of random letters. In Experiments 1 and 2, participants completed both high prevalence (50%) and low prevalence (4%) blocks in a counterbalanced order. The critical manipulation involved providing false feedback to some participants during the low prevalence condition: on 20% of target-absent trials where participants correctly indicated 'target absent', they were falsely told that they had missed a target. This manipulation inflated participants' perceived miss rates by approximately 20%. Results showed that false feedback successfully reduced the LPE. Participants in the false feedback condition detected significantly more targets compared to the true feedback condition, although this came at the cost of increased false alarms. SDT analyses confirmed that false feedback shifted participants' decision criterion toward a more liberal position without significantly changing sensitivity. These findings support the hypothesis that individuals attempt to equate the numbers of misses and false alarms they commit, and that manipulating perceived error rates through feedback can influence search performance.

A related finding has been reported by Wolfe (2022) who conducted a large online study where 803 participants rated skin lesions as melanoma or nevus using a medical image labelling application. Each block had 80 images with either high (50%) or low (20%) target prevalence, with or without feedback. The study examined how experience in one block influenced performance in subsequent blocks. The key finding was that feedback in the low prevalence blocks made participants adopt more conservative decision criteria in subsequent blocks. In contrast, feedback in the high prevalence blocks made their decision criteria more liberal.

Feedback does seem to make decision criteria more conservative in low prevalence search, however, somewhat surprisingly, there is no evidence that feedback increases the extent of searching itself. Drew and Williams' (2017) study used the search paths generated from eye-tracking to provide feedback to help participants recognise when they were terminating search prematurely, whilst searching for simple targets (oval/rectangle) in outdoor scenes or synthetic textures. Six experiments were conducted testing various eye movement feedback (EMF) methods during visual search for rare targets (10% prevalence). These methods included removing semi opaque overlay as areas were fixated, adding overlays once fixations left areas, and automated EMF. The results showed no reliable performance benefits from any of the EMF manipulations.

Taken together, these findings paint a consistent picture: the LPE is robust, replicable, and resistant to many attempted interventions, but it is not immutable. The magnitude of the effect varies as a function of working memory capacity, age, expertise, and the nature of feedback provided. Critically, the persistence of the LPE across both novices and professionals, and across a wide range of task types, suggests that the underlying mechanisms - conservative shifts in both selection and identification thresholds - operate at a level not easily overridden by strategic intent alone (Wolfe and Van Wert, 2010). This has important implications for the present thesis: if prevalence-induced attentional biases are resistant to strategic control within a single task, it becomes important to understand whether they also propagate across task boundaries into subsequent visual events.

The Effect of Target Prevalence on Visual Attention

The previous section described the behavioural features of the LPE on target detection, and the fact that whilst it is pervasive, its magnitude may be subject to individual variation and strategic mitigation. A less reported feature of the LPE is its effect on visual attention. In this section I explore how target prevalence affects both the focus, and spatial distribution of, visual attention.

The human visual system is unable to process into conscious awareness all the information present in the visual field. Visual attention is used to direct the allocation of cognitive resources to both space and objects. Many decades of research have explored how visual attention is directed towards space and objects and how decisions are made about the spaces and objects that are attended.

Visual attention operates through multiple interacting systems that determine how attentional resources are allocated across time, space, objects and events. In doing so, visual attentional processes enable us to anticipate, select, process and prioritise our behaviours. Bottom-up visual attention refers to the mechanisms by which stimuli capture attention based on physical properties like colour, motion, or contrast (Theeuwes, 2010; Yantis & Egeth, 1999). This system is stimulus-driven, experience independent and reflects the visual system's sensitivity to the presence of simple features. Top-down visual attention reflects the needs required to meet current goals, instructions, and task demands (Egeth & Yantis, 1997; Posner, 1980). Top-down visual attention can, at some cost (Lavie, 1995), help us resist visual distraction through focussing attention. Bottom-up visual attention operates quickly, whereas top-down visual attention operates more slowly.

Perceptual Load Theory (PLT) (Lavie, 1995; Lavie, 2005; Lavie & Tsal, 1994) suggests that the cognitive demands of a primary task dictate how extensively irrelevant distracting elements are cognitively processed. When a primary task requires minimal cognitive resources (low task load conditions), excess capacity remains available to process distractors, leading to interference effects. Conversely, when the primary task consumes all available cognitive resources (high task load conditions), distractor processing can be reduced or eliminated.

The processes of visual attention can, therefore, be divided into bottom-up and top-down processes that respond quickly to sensory signals and more slowly to cognitive information. However, to do so risks being overly simplistic. The knowledge and expectancies that influence top-down visual attention can be gleaned from learning processes that operate by information accumulation over time. The knowledge and expectancies of the regularities about both the environment, and the items occurring within it, can be explicitly and/or implicitly acquired (Awh et al., 2012; Failing & Theeuwes, 2018). It is from these processes that the top-down visual attention system can become attuned to reflect the statistical regularities of what is being experienced. I now turn to the question of whether one such environmental regularity, prevalence, might influence top-down visual attention.

In contrast to the bottom-up visual attention system, the top-down visual attention system results in attention being more, or less, focussed on a location or an object. The need to focus attention results from limitations of both peripheral and foveal vision. By peripheral vision, I refer to the dramatic decline in visual resolution from the fovea to the periphery. Foveal vision benefits from more cortical processing power than peripheral vision (Duncan & Boynton, 2003), reflecting the rapid decrease in photoreceptor density away from fixation (Curcio et al., 1990).

Importantly, attention shows a bias towards foveal vision that goes beyond what visual acuity alone would predict. More attentional resources are allocated to the locations of visual fixations (Van Heusden et al., 2023), and less to peripheral vision than acuity constraints alone would suggest (He et al., 1996; Intriligator & Cavanagh, 2001; Wolfe et al., 1989). There is also evidence that humans have poor insight into their ability to respond to objects appearing in peripheral vision - an effect referred to as subjective inflation (Odergaard et al., 2018).

One account that considers how factors that affect top-down attention influence the size of the attentional window comes from Hulleman and Olivers (2017). Hulleman and

Olivers proposed the Functional Viewing Field framework (FVF) to understand how attentional resources are spatially distributed during visual tasks (Figure 1.2). The FVF represents the dynamic area around fixation where visual information can be effectively processed, with its size determined by the interaction between sensory limitations and task demands. Importantly, the FVF is not under voluntary control but emerges from the requirements of a particular visual task.

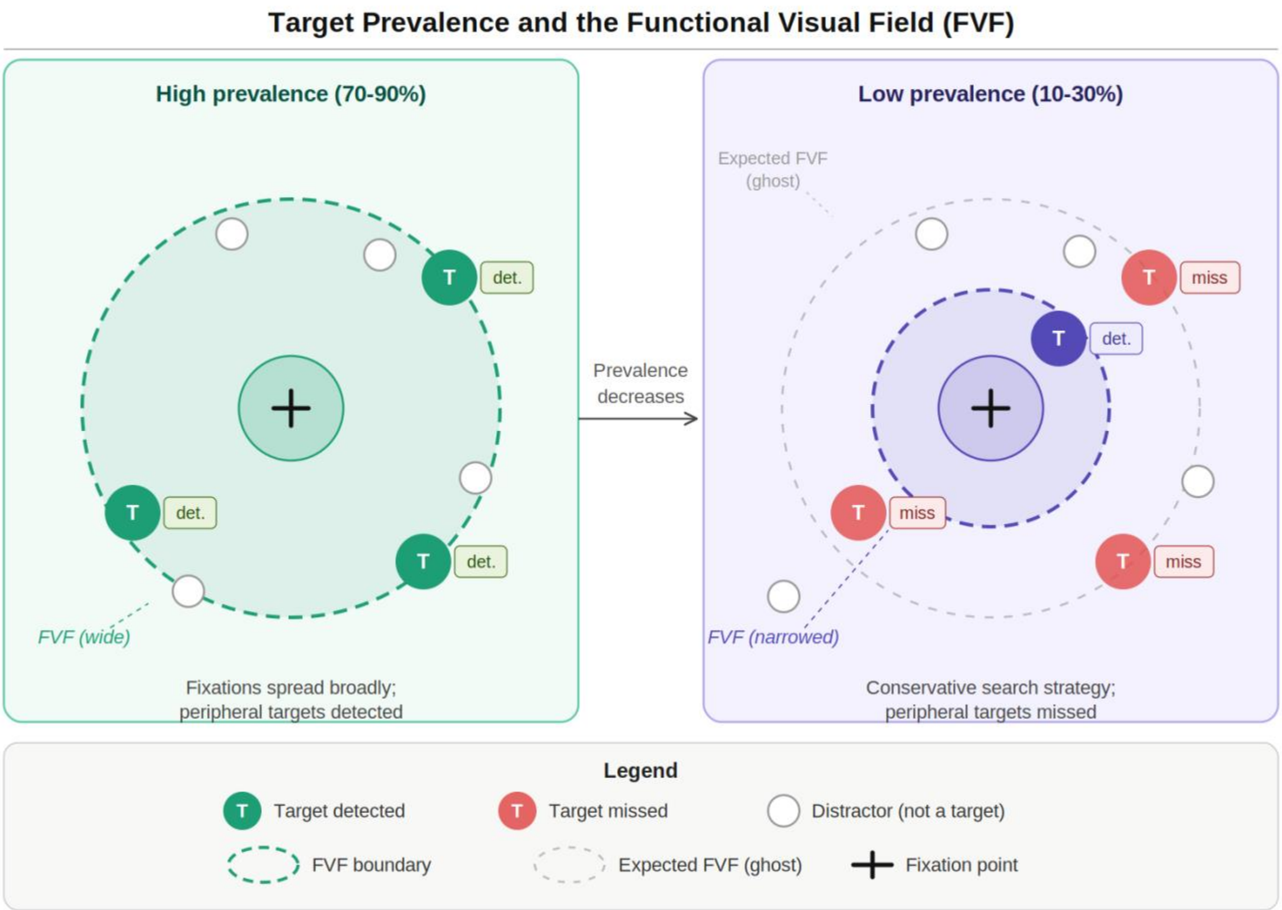


Figure 1.2. *Schematic representation of the Functional Visual Field (FVF) under high and low target prevalence conditions (Hulleman & Olivers, 2017).* Under high prevalence the FVF is broad and peripheral targets are detected. Under low prevalence the FVF narrows, concentrating attentional resources near fixation and leaving peripheral targets outside the effective attentional window, resulting in misses.

Understanding how this framework operates in practice requires examining the specific mechanisms that govern the size of the FVF and its relationship to the difficulty of target detection. The framework proposes that items within the spatial extent of the FVF are processed in parallel. Furthermore, it is proposed that the size of the FVF is determined by the interaction between retinal and cortical constraints, in addition to task demands. The primary factor impacting the size of the FVF is the ease of target detection, with targets that are harder to detect resulting in smaller FVFs. This reduction in the size of the FVF is thought to either reduce interference from distractors (Shamsi et al., 2021), or to increase resolution within the attended area.

Further empirical work provides support for the role of spatial attention in shaping the effective visual field. Young and Hulleman (2013) investigated how the spatial spread of attention varies with search difficulty using a gaze-contingent visual search paradigm. Their findings confirmed that the FVF contracts under high attentional demand, with detection rates dropping more steeply in peripheral than central regions under demanding conditions. These findings provide direct empirical support for the FVF framework and are consistent with the proposal that low prevalence conditions, by increasing attentional demands, may produce a corresponding narrowing of the effective attentional window. This is directly supported by Pinto and Papesh (2024), who found that high target prevalence itself reduced the spread of attention during search, providing further evidence that prevalence modulates attentional breadth.

Hulleman and Olivers (2017) did not link the FVF to the LPE directly. However, a link was made by Menneer et al. (2017) in the commentaries associated with the Hulleman and Olivers paper. Menneer et al. (2017) presented reanalysed data showing that fixations in high and low prevalence search were clustered differently around fixation, particularly in the early stages of search. The difference being that the number of fixations increased with target prevalence (the data were normalised for the total number of fixations). The data presented by Menneer et al. (2017) are far from definitive, but they are consistent with the idea that prevalence might impact the size of the FVF used to detect targets presented away from fixation.

Recent research by Olivers (2025) has provided extensive evidence supporting the dynamic relationship between attention and spatial distribution across the visual field. This work demonstrates that attention and eccentricity are fundamentally interconnected, with attention serving as a mechanism that partially compensates for the limitations of peripheral vision by effectively expanding the FVF. Olivers' review reveals that attention shows a pronounced central bias, with target detection performance being influenced more by the spatial relationship between targets and fixation than by their absolute distance from the centre of gaze. This central bias is particularly relevant to understanding prevalence effects, as it suggests that attention naturally prioritises central locations, potentially creating spatial constraints that interact with prevalence-induced changes in attentional deployment.

Furthermore, Olivers (2025) provides evidence for attention narrowing under high cognitive load, where attention contracts towards central vision when task demands increase. Given that low prevalence conditions create additional cognitive demands through increased uncertainty and more conservative decision criteria, this attentional narrowing effect may represent another mechanism through which prevalence influences the spatial distribution of attention. The finding that demanding central tasks increase the tendency for attention to favour central locations suggests that the cognitive demands associated with processing low prevalence targets may systematically reduce the spatial extent of attention available for detecting subsequent targets, regardless of their location.

Olivers' research also reveals that although attention mechanisms remain relatively constant across eccentricity, their effects vary considerably depending on task demands and stimulus properties. This finding has important implications for understanding how prevalence effects might transfer across different spatial locations, as it suggests that prevalence-induced changes in attentional state may have differential effects on target detection depending on where subsequent targets appear in the visual field.

Research has also shown that attention narrows during more difficult search tasks, requiring a greater number of fixations and more concentrated spatial sampling, whereas easier 'pop-out' search allows attention to be spread more broadly across the visual field (Hulleman et al., 2020; Papesh et al., 2021). This task-dependent modulation of spatial attention has direct implications for understanding how prevalence might affect search performance. The increased task difficulty associated with rare target detection leads to a reduction in the size of the FVF, creating a spatial constraint on attention precisely when broader coverage would be most beneficial.

In summary, the studies discussed above have examined how visual attention is guided by both bottom-up and top-down factors. Top-down factors influence how visual attention is spatially distributed and focussed for a particular task. The FVF framework conceptualises how visual attention is distributed, considering the constraints of the human visual system and the dynamic nature of task demands. As the FVF has been shown to narrow during difficult search tasks, and given the data presented by Menneer et al. (2017), I suggest that target prevalence is a factor that may influence the size of the FVF. Therefore, I add the size of the FVF as a potential marker of the LPE to those described earlier in the Chapter.

The Effect of Target Prevalence on Responding to Subsequent Events

In the previous sections, I have established that low prevalence significantly influences target detection through influencing search and identification decision thresholds, and the size of the functional visual field. However, by definition, prevalence is a property of events that unfold across time: for a target to be rare or frequent, it must appear and be detected (or missed) on multiple occasions. This temporal dimension raises an important question that goes beyond the individual trial: how does the accumulating experience of encountering low prevalence targets — building up trial by trial — affect the way attention is deployed to subsequent visual events? To address this, I now consider the behavioural consequences of detecting a low prevalence target.

Evidence that target prevalence affects subsequent behaviour comes from literature exploring the cognitive and electrophysiological responses seen on a subsequent trial, a phenomenon known as post-error slowing (PES; Rabbitt, 1966). This literature is relevant to understanding the LPE as errors are more commonly made to low prevalence targets. As such, the effects of PES will be more common in low prevalence conditions.

An important precursor to the post-error slowing literature in visual search is Chun and Wolfe (1996), whose 'Just Say No' model proposed that search termination is governed by a decision rule determining when to respond 'target absent'. In low prevalence conditions, this threshold is lowered - observers quit searching earlier - accounting for a substantial proportion of low prevalence misses. The model links the decision to terminate search directly to the accumulation of absent responses over time, providing a mechanism by which prevalence history shapes subsequent behaviour. This line of thinking is incorporated in current iterations of Guided Search (Wolfe, 2021), in which the quit threshold is modelled as a dynamic parameter adjusting based on recent history. In current forms, Guided Search includes an explicit representation of attentional processing bottlenecks, whereby commitment of resources to one target delays processing of subsequent stimuli - directly relevant to the sequential prevalence effects investigated here.

PES has been observed across multiple paradigms demonstrating that participants performing serial response time tasks showed PES, with responses following errors being considerably slower than average correct responses (Rabbitt, 1969; Rabbitt & Rodgers, 1977). PES has also been observed in studies using the Flanker task (where participants respond to a central target stimulus while ignoring surrounding 'flanker' stimuli; Wild-Wall et al., 2008), the Simon task (where participants respond to a non-spatial feature of a stimulus while the stimulus appears in different spatial locations; Simon & Small, 1969), and the Stroop task (where participants name the ink colour of colour words while ignoring the word's meaning; Danielmeier & Ullsperger, 2011).

Dutilh et al. (2012) identified five potential mechanisms that have been proposed to explain the behavioural adaptations that occur after making a rare error. First, perceptual distraction occurs when errors caused by infrequent or unexpected events disrupt the processing of subsequent stimuli (Notebaert et al., 2009). Second, time may be wasted on irrelevant processes, delaying evidence accumulation on following trials (Rabbitt & Rodgers, 1977). Third, individuals may develop a bias against the response option they selected incorrectly (Laming, 1968). Fourth, individuals may gain better control over when information accumulation begins following an error (Laming, 1968). Finally, increased response caution may emerge, whereby errors prompt individuals to raise their response thresholds (Botvinick et al., 2001). In a similar vein to accounts of the LPE, PES is believed to reflect the adoption of a more conservative decision-making approach following an error in an attempt to reduce the chance of making further errors.

It is an open question however, as to how effectively decision criteria are adjusted when responding to an error. Research using Flanker tasks has shown that although participants consistently slow down after errors, this slowing is not always accompanied by improved accuracy, with some studies reporting error rates that remain elevated or even increased on post-error trials. Similarly, studies using choice response time tasks have found that PES can occur without compensatory improvements in performance, suggesting that slowing following an error may reflect disruptive rather than adaptive processes (e.g., Hajcak et al., 2003; Hajcak & Simons, 2008; Laming, 1979; Rabbitt & Rodgers, 1977).

Of relevance to the LPE, Notebaert et al. (2009) showed that PES, and the behavioural consequences assumed to follow from errors, can also follow rare correct responses when task conditions allow. Notebaert et al. had participants perform a speeded 4-AFC (four alternative forced choice) colour categorisation task where the difficulty of the categorisation was achieved by varying colour intensity according to a psychophysical staircase procedure. The staircase procedure allowed stimulus conditions to be created whereby most responses were correct or most responses were incorrect. Participants received feedback on all trials indicating that a correct or an incorrect response had been made. The critical finding reported by Notebaert et al. was that they observed slowed response times following rare events, including rare events that were responded to correctly. Notebaert et al. proposed that unexpected responses, whether correct or incorrect, led to an orienting response that draws resources from subsequent trials. The implication of this finding for understanding the LPE is important: behavioural changes to the appearance of low prevalence targets might occur whether they are correctly detected or not. Cognitive Control Theory (CCT; Shiffrin & Schneider, 1977; see also Attentional Control Theory, ACT; Eysenck et al., 2007) supports the interpretation given by Notebaert et al. CCT suggests that performance is continually monitored to detect errors. When unexpected events occur, ongoing cognitive processes are disrupted leading to attentional resources being temporarily diverted away from the subsequent task.

The behavioural effects observed following rare targets raise a fundamental question about whether these adaptive responses extend beyond the immediate task context to influence subsequent unrelated judgements. Although the immediate consequences of encountering rare targets manifest as increased response times and errors, the influence of target prevalence may extend beyond these immediate behavioural adjustments to influence how individuals' approach and evaluate subsequent stimuli, even when those stimuli are unrelated to the original task context.

The study of target detection usually consists of tasks whereby visual attention can be given to a single task. However, in the real world, tasks requiring the detection of visual targets often require shifts between multiple perceptual judgements. Understanding how limited attentional resources are divided between tasks occurring in close temporal proximity is an important problem to understand. I argue that this is especially so when responses to a primary task may be subject to the influence of target prevalence.

The dual-task cost refers to a specific set of conditions when two tasks need to be performed concurrently. In dual-task studies, concurrent task performance is compared to performance on each task individually (Pashler, 1994). For example, early research demonstrated that performing a verbal memory task concurrently with a visual tracking task resulted in worse performance on both tasks compared to single-task conditions (Kerr, 1973). Dual-task interference has been replicated across a variety of task pairings, including verbal and spatial tasks, auditory and visual tasks, and reaction time and recall or recognition tasks (Pashler & Johnston, 1998). When dual tasks require focussed attention at different points in time, individuals must switch their attention between tasks, incurring costs in terms of efficiency and performance (Monsell, 2003). This switching burden is influenced by task modality, with tasks involving different sensory modalities being generally easier to perform concurrently because they draw on separate resource pools,
whereas tasks within the same modality compete directly for the same resources.

Exploration of the temporal constraints on attentional allocation have been explored using the Attentional Blink (AB) paradigm whereby participants respond to two targets presented at different points in a RSVP stream. The key variable is the effect of the temporal interval between targets on their detection. Raymond et al. 's (1992) study demonstrated that participants could accurately identify a partially specified letter target but showed poor detection of a fully specified probe letter when presented within a 270 ms interval beginning 180 ms after the offset of the target. Control conditions were included by

Raymond et al. to confirm that this deficit was not due to perceptual masking or simply requiring participants to identify the target, establishing the attentional nature of the phenomenon. The AB reveals the bottlenecked nature of conscious awareness, where engagement of attention to processing one stimulus can cause subsequent stimuli to fail to reach conscious perception, despite being clearly visible and task relevant. The magnitude of the AB is influenced by various factors including the difficulty of processing the first target, the similarity between targets and distractors, and importantly, the characteristics of the targets themselves (Dux & Marois, 2009).

Research using cross-modal presentations reveals that the AB is not limited to a single sensory modality. Arnell and Jolicœur (1999) found that when participants had to detect targets presented in different modalities, for example, an auditory first target followed by a visual second target, or vice versa, they still experienced significant AB effects. These cross-modal AB findings indicate that the phenomenon stems from central processing limitations rather than constraints within specific sensory systems. The results suggest that attention operates as a capacity-limited system whereby processing resources must be strategically allocated. When stimuli are more cognitively demanding to process, they consume more of these limited resources, leading to stronger interference effects.

Like the AB, the Psychological Refractory Period paradigm (PRP; Pashler, 1984, 1994; Welford, 1952) typically involves presenting two stimuli requiring speeded responses in rapid succession, with stimulus onset asynchrony (SOA) serving as the independent variable, and response time to the second stimulus as the dependent variable. Research shows that the shorter the SOA between the first and second stimulus, the longer the response time to the second task, indicating a processing bottleneck where central processing of the second stimulus must wait until processing of the first stimulus is completed (Pashler, 1994).

Theoretical accounts suggest that this processing bottleneck involves the timing of response initiation rather than response selection, with the bottleneck occurring at a stage that programs the timing of response onset immediately prior to responding (Klapp et al., 2019). PRP paradigms have been used to examine how the difficulty of a first task influences the magnitude of interference with a second task. When the first task is more demanding, either due to increased perceptual difficulty or higher cognitive load, the PRP effect becomes more pronounced (Levy & Pashler, 2001).

Evidence from driving simulation studies has demonstrated that PRP effects persist even when both tasks are ecologically relevant. In a study by Wechsler et al. (2022), participants in a driving simulator had to warn pedestrians against crossing the street and brake when the lead car braked, showing longer braking response times when required to concurrently perform pedestrian warning tasks. Results showed that the PRP effect was larger when both tasks were ecologically relevant compared to studies where only the second task was realistic, suggesting that ecologically relevant first tasks result in stronger interference with subsequent tasks.

Importantly for the current thesis, at least one study has explored the AB with respect to target prevalence. Papesh and Guevara Pinto's (2019) study used pupillometry to index attentional engagement across two experiments. They manipulated how often participants encountered the first target, then measured the effects on detecting the second target. Results showed that when participants successfully detected rare targets, they were less likely to spot subsequent targets. What Papesh and Guevara Pinto's (2019) study reveals, therefore, is the additional attentional demands associated with detecting rare targets.

The findings reviewed above demonstrate that detecting targets, particularly rare ones, consumes attentional resources with consequences for temporally subsequent stimuli presented in rapid succession. A parallel line of research examines what happens when multiple targets must be detected within the same search, revealing a phenomenon known as subsequent search misses (SSM). Although SSM research focuses on detecting multiple targets within a single display rather than across temporally separate tasks, the cognitive mechanisms proposed to explain these errors provide important insights into how detecting a target might influence subsequent visual judgements.

SSM (originally termed 'satisfaction of search' in the radiological literature) refers to the observation that detection accuracy for a second target decreases significantly after an initial target has been found within the same display (Adamo et al., 2013). This effect was first documented by Tuddenham (1962), who observed that radiologists were more likely to miss an abnormality when another abnormality had already been identified. The initial explanation for this phenomenon posited that observers became 'satisfied' after finding the first target and prematurely terminated their search. However, subsequent eye-tracking research has demonstrated that searchers continue to search after finding an initial target (Fleck et al., 2010), indicating that premature termination alone cannot fully account for SSM errors. This led to the adoption of the term 'subsequent search misses' to avoid theoretical assumptions about the underlying causes.

Understanding SSM is relevant to the current thesis for two reasons. First, the mechanisms proposed to account for SSM suggest that cognitive limitations do not reset between target detections but rather persist and influence subsequent processing. If detecting a first target within a single display impairs detection of a second target in that same display, similar resource limitations may impair performance when targets must be detected across sequential, separate tasks. Second, research has demonstrated that SSM interacts with target prevalence, with low prevalence of dual-target trials increasing SSM errors. This interaction suggests that prevalence effects extend beyond individual target detection to shape expectations and search strategies that influence subsequent behaviour.

Several theoretical accounts have been proposed to explain SSM effects, each highlighting different cognitive mechanisms. The resource depletion account suggests that maintaining information about the first-found target in visual working memory depletes cognitive resources necessary for detecting subsequent targets, though dual-task studies testing this hypothesis have yielded mixed results (Cain & Mitroff, 2013; Gorbunova et al., 2019). The perceptual set account proposes that detection of the first target creates a perceptual bias towards targets with similar features whilst reducing sensitivity to dissimilar targets, with this similarity effect extending beyond purely perceptual features to encompass categorical and conceptual similarity (Biggs et al., 2015; Gorbunova, 2017). Most recently, the attentional template account (Adamo et al., 2021) provides a unifying framework suggesting that the first target becomes an attentional template maintained in working memory, creating interference with subsequent target detection because the cognitive resources necessary for target recognition overlap with those required for template maintenance. Despite their differences, all three accounts converge on the idea that detecting an initial target consumes cognitive resources and creates attentional states that persist beyond the moment of detection, with implications for understanding how target detection in one context might affect performance in subsequent tasks.

The relationship between SSM and target prevalence has emerged as an important area of investigation. Menneer et al. (2010) examined the interaction between prevalence effects and dual-target costs in visual search. Their findings revealed that the prevalence effect was more pronounced in dual-target search compared to single-target search, with the dual-target cost being larger under target prevalences that differed from 50%. This interaction suggests that prevalence and dual-target search may place compounding demands on decision processes. Godwin et al. (2010a) provided additional evidence for this interaction in the context of X-ray threat detection, manipulating the relative prevalence of different target types (Target A: 45% prevalence; Target B: 5% prevalence). They found that both the dual-target cost and the prevalence effect contributed to performance decrements when searching for targets with different prevalence rates. In contrast, Godwin et al. (2010b) found no interaction between the dual-target cost and overall prevalence effect in X-ray search, though they observed that the response criterion in dual-target search did interact with target prevalence.

Subsequent research has demonstrated that the relative prevalence of dual-target trials specifically influences SSM rates. Cheng and Rich (2018) manipulated both set size and the prevalence of dual-target trials in a multiple-target search task. Participants searched for two targets (either zero, one, or two present) amongst distractors. The critical finding was that low prevalence of dual-target trials increased SSM errors relative to high prevalence conditions, whilst the prevalence of dual-target trials did not affect accuracy on single-target trials. This finding suggests that individuals may develop expectations about the likelihood of multiple targets co-occurring, which in turn influences their search strategies and subsequent target detection. When dual-target displays are rare, individuals may be less likely to continue searching after finding an initial target, as their expectations are biased towards single-target displays.

The perceptual set account of SSM relates to the prevalence effect through the concept of expectation and statistical learning. Just as low prevalence reduces the probability of detecting rare targets through shifts in decision criteria and quitting thresholds, individuals may be less likely to search for additional targets when dual-target displays are themselves rare. This expectation-based mechanism may operate alongside perceptual priming and attentional guidance processes to produce the observed pattern of SSM errors. Evidence suggests that both target repetition effects and target expectation contribute to how prevalence shapes search behaviour, with repeated exposure to particular prevalence conditions strengthening expectancy-based performance adjustments (Godwin et al., 2016). The statistical structure of the environment therefore influences not only whether observers detect individual targets, but also whether they continue searching for additional targets after an initial detection.

The SSM literature establishes that multiple-target search involves cognitive costs beyond those observed in single-target search, and critically, that these costs interact with target prevalence. The mechanisms proposed to explain SSM—resource depletion, perceptual set, and attentional template activation—all suggest that detecting a target, particularly a rare target, consumes cognitive resources and creates attentional states that persist beyond the immediate moment of detection. Whilst SSM research has primarily focused on detecting multiple targets within a single display, these mechanisms provide a foundation for understanding how detecting a target in one task might affect performance in a subsequent, separate task. The finding that rare dual-target trials increase SSM errors suggests that statistical regularities influence not only immediate target detection but also expectations about subsequent events. When targets are rare in one task and observers must subsequently perform another visual search, the combined effects of low prevalence and SSM-like resource limitations may compound, leading to elevated miss rates and altered decision criteria in the subsequent task.

When attention needs to be distributed across multiple tasks, there are competing theoretical frameworks that offer different predictions about the allocation of attentional resources. The capacity-sharing model (Tombu & Jolicœur, 2003) proposes that cognitive resources operate as a flexible pool that can be redistributed between tasks. Under this account, if a primary task requires fewer resources due to easier processing demands, the surplus capacity becomes available for allocation to a secondary task, potentially improving performance. This redistribution mechanism suggests that factors influencing the cognitive demands of an initial task should directly impact performance on subsequent tasks.

In contrast, the economic processing model (Navon & Gopher, 1979) posits that resource savings from an easier primary task are not automatically transferred to benefit secondary task performance. Instead, any efficiency gains serve primarily to reduce the overall cognitive load without necessarily enhancing subsequent attentional engagement. These competing theoretical frameworks provide different predictions about how prevalence effects in one task might influence performance on subsequent tasks. These competing predictions highlight a critical gap: existing single-task prevalence research cannot adjudicate between these theoretical frameworks, necessitating sequential task paradigms to test their differential predictions.

A further factor relevant to understanding prevalence effects on subsequent task performance is the role of boredom and mind wandering. Low prevalence visual search tasks are inherently monotonous: participants must maintain vigilant attention across many trials in which targets rarely appear. This sustained attention demand creates conditions known to elicit both boredom (Eastwood et al., 2012) and task-unrelated thought, or mind wandering (Smallwood and Schooler, 2006). Mind wandering involves a decoupling of attention from the immediate perceptual environment, with attentional resources redirected toward internally generated thought (Smallwood et al., 2008). Critically, mind wandering has been shown to impair perceptual processing of external stimuli (Smallwood et al., 2008; Unsworth and McMillan, 2014), reduce response accuracy and increase response times (McVay and Kane, 2009), and reduce sensitivity to rare or unexpected events (Bastian and Sackur, 2013).

In summary, in this section I have explored how low prevalence targets affect behavioural responses following their appearance. It has been established that when a low prevalence target is encountered, two things happen: detection and identification errors increase, and attentional allocation is disrupted. It follows then, that the disruption of attention following low prevalence stimuli is therefore likely to affect how attention is allocated to a subsequent task.

Low prevalence targets generate variable responses, creating inconsistent effects - sometimes influencing PES, and sometimes not. This variability complicates the establishment of stable decision thresholds and extends beyond individual trial boundaries, making effective attentional recalibration increasingly challenging. When sufficient time exists between tasks, the visual system can overcome this variability and recalibrate effectively. However, a critical question emerges from this point: How do the cognitive consequences of prevalence-biased processing in an initial visual judgement influence performance on subsequent perceptual decisions occurring in close temporal proximity? It is this fundamental question that forms the core investigation of the studies presented in this thesis.

The Neural Mechanisms Underlying Prevalence Effects

So far in this chapter, I have established that low prevalence targets result in poorer detection and identification than more frequently occurring targets. In doing so, I have outlined how low target prevalence affects the spatial distribution of visual attention, establishing that low prevalence results in a reduced functional viewing field. Additionally, I have shown that low prevalence targets can also disrupt attentional allocation to subsequent visual events. To understand how prevalence effects might transfer between tasks, we now need to examine the neural mechanisms underlying the behavioural markers of the LPE.

Before reviewing the neural evidence, it is worth noting that the application of electrophysiological methods to the study of the low prevalence effect is remarkably limited. Despite decades of behavioural research establishing the LPE as a robust and theoretically important phenomenon, very few — if any — published studies have directly examined the ERP correlates of prevalence effects in visual search tasks. This is a notable gap in the literature, given the well-established sensitivity of the P3 component to stimulus probability and attentional capture (Polich, 2007). The current thesis therefore makes a novel contribution not only in examining sequential prevalence effects behaviourally, but in providing one of the first direct electrophysiological investigations of the neural mechanisms underlying the LPE.

Examining event related potential (ERP) components generated by the brain during visual tasks can provide a more in depth understanding of the mechanisms underlying these behavioural effects. Of relevance to the LPE is the P3 ERP component, as its amplitude is thought to directly reflect the cognitive resources consumed during target processing (Polich, 2007). First described by Sutton and colleagues in 1965, the P3 is characterised by a positive deflection occurring approximately 300–600 ms following stimulus onset. The P3 encompasses two distinct subcomponents with neuroanatomical separation reflecting their cognitive functions. The P3a is generated in frontal brain regions and mediates rapid attentional capture and novelty detection. In contrast, the P3b originates from parietal occipital brain regions, aligning with its functional role in target detection and working memory updating. However, the interpretation of P3 findings involves considerable complexity and some conflicting results that must be carefully considered when drawing conclusions about the underlying neural mechanisms of the LPE.

The foundation of P3 research in prevalence effects stems primarily from the 'oddball paradigm' - an experimental approach that predates modern LPE studies by several decades. In the oddball task, participants are presented with a continuous stream of frequent 'standard' stimuli interspersed with rare 'target' stimuli (e.g., Duncan-Johnson & Donchin, 1977; Squires et al., 1976). Data from these studies, reviewed by Verleger (2020), showed that the P3 was larger following rare rather than standard targets. Presumably, the larger amplitude for low prevalence targets reflects the increased processing effort associated with their identification (see O'Connell et al., 2012). There is evidence, therefore, that low prevalence targets should elicit larger P3 amplitudes compared to high prevalence targets.

The working assumption is that the behavioural costs in detection accuracy and response times observed in LPE studies correlate with the magnitude of the P3, though this has never been formally tested. Whilst studies generally support this idea, there has been research which suggests that it may not be the rarity of stimulus appearance, but other factors associated with the appearance of a rare target that cause observable changes in the P3. For example, Wascher et al. (2020) investigated P3b amplitude using a modified continuous performance task where participants monitored continuous letter sequences. The task involved (A or B) and (X or Y) pairs, with letter X requiring a key-press response. X occurred in 80% of trials following A and in 20% of trials following B (with the reverse pattern for Y). Despite this difference in target probability, P3b amplitudes were equally large for both probable and improbable occurrences of X. The only factor affecting P3b amplitude was SOA, with P3b being larger in 2000 ms compared to 1500 ms intervals. This finding suggests that P3b responses primarily reflect the temporal interval between target stimuli rather than their probability of occurrence per se (see also Kamp et al., 2020).

In addition to its role in target processing, the P3 is also associated with attention, particularly where and how attention is deployed. The anatomical distinction between P3 subcomponents explains how prevalence affects the deployment of spatial attention. The parietal-occipital networks supporting P3b responses are closely associated with the dorsal attention network, primarily involved in goal-directed attentional control and the control of the allocation of spatial attention (Corbetta & Shulman, 2002). When individuals deploy spatial attention to expected target locations, these parietal networks support rapid target detection. However, when spatial uncertainty increases, the attentional system shifts to frontal processing networks. These frontal processing networks are associated with P3a responses (Ponomarev et al., 2025), as might be the case with low prevalence targets appearing in unpredictable locations, therefore, the P3a is likely to be particularly sensitive to target prevalence.

The studies discussed so far in this section suggest that target prevalence modulates both spatial and temporal uncertainty in attentional processing. High prevalence targets, by virtue of their frequent occurrence, may establish predictable temporal patterns that could allow for more efficient spatial attention deployment to likely target locations. Conversely, low prevalence targets may appear unpredictably across both space and time, increasing uncertainty. The P3 provides a neural index of how attention is allocated in response to this prevalence-induced uncertainty. It can therefore be surmised that changes in the P3 are likely driven by prevalence.

The P3 has been linked to prevalence-induced changes in target processing and attention, however it is also important when considering the effects of prevalence on subsequent tasks. The link between the P3 and prevalence effects on sequential tasks comes from dual-task research, demonstrating that P3 amplitude serves as an index of attentional resource competition. Isreal et al. (1980) demonstrated that P3 amplitude for a secondary auditory discrimination task decreased as demands increased in a primary visual tracking task, providing neural evidence for resource competition between concurrent tasks.

Kramer et al. (1985) extended these findings with a more complex design manipulating four factors: inter-task redundancy, spatial proximity of displays, perceptual object unity, and resource demands, with results again showing decreased secondary task P3 amplitude with increased primary task difficulty. Wickens et al. (1983) provided additional evidence for resource competition effects through systematic examination across different stimulus modalities (visual vs. auditory) and response requirements (manual vs. vocal), demonstrating that resource allocation and interference patterns varied with task similarity, with greater interference when tasks competed for similar processing resources. Dell'Acqua et al. (2005) extended these findings to sequential processing through investigation of the PRP effect. When two sequential targets were presented at varying intervals (50–900 ms), P3 responses to the second target showed both reduced amplitude and delayed onset at short intervals, providing evidence for a central processing bottleneck where initial target processing creates delays in processing subsequent targets.

Together, these findings indicate that when cognitive resources are consumed by a primary task, fewer resources remain available for concurrent or subsequent processing. The change in availability of resources for secondary tasks is reflected in the amplitude of the P3. These dual-task resource competition effects parallel how low prevalence targets disrupt attentional allocation to subsequent visual events: when low prevalence processing consumes cognitive resources, fewer resources remain available for processing subsequent stimuli, creating sequential task deficits.

In summary, the research discussed in this section provides a mechanistic framework for understanding both single-task prevalence effects and their proposed propagation across sequential tasks. Evidence from ERP studies shows that the shifts to identification thresholds, changes in the allocation of spatial attention and consequences for responses to subsequent tasks all have electrophysiological neural markers. These electrophysiological markers are linked to prevalence-related changes in the P3. As such, the evidence for target prevalence influencing responses to current and subsequent visual events is both behavioural and electrophysiological.

Summary and Direction of this Thesis

In this chapter, I have established the theoretical foundation of the LPE by examining how target prevalence influences behavioural responses, spatial attention allocation, and behavioural adaptations affecting the processing of subsequent visual events. I have also established the neural correlates associated with these effects.

The experiments in this thesis explore how target prevalence in one visual discrimination task affects performance on a subsequent, distinct visual task. This research question extends beyond traditional single-task prevalence studies by examining whether prevalence-induced changes in attentional state persist and transfer across task boundaries. The experiments presented in Chapters 2–4 employ a common sequential task paradigm with participants first performing a letter discrimination task, closely followed by a dot-probe detection task.

The experimental paradigm offers three advantages for testing competing theoretical accounts of prevalence effects. First, by manipulating prevalence exclusively in the letter discrimination task whilst holding dot-probe characteristics constant, the paradigm isolates how statistical regularities in one context affect processing in another, allowing exploration of accounts that predict local (task-specific) versus global (cross-task) prevalence effects. Second, the spatial properties of the dot-probe task, particularly the systematic manipulation of eccentricity, allow for direct testing of the FVF framework's prediction that prevalence-induced attentional narrowing should differentially affect processing of stimuli presented either near or far from fixation. Third, the rapid sequential nature of the paradigm is ideally suited for examining resource depletion accounts, as it captures the immediate consequences of target detection before attentional resources have time to recover.

The letter discrimination task serves multiple functions: it manipulates target prevalence to induce different attentional states, varies task difficulty to test resource demands, and provides trial-by-trial feedback to examine the role of explicit performance awareness. The dot-probe task serves as a neutral, standardised measure of attentional resource availability and spatial distribution, with its simplicity ensuring that any observed effects reflect carryover from the letter discrimination task rather than the complexity of dot-probe detection itself. The critical dependent measure is how dot-probe detection performance (both accuracy and response time) varies as a function of preceding letter discrimination prevalence, difficulty, and eccentricity conditions.

The MDM framework (Wolfe & Van Wert, 2010) suggests that low prevalence induces conservative shifts in both selection and identification criteria. Applied to the current sequential paradigm, the MDM predicts that participants' conservative criteria adopted during low prevalence letter discrimination should create a cognitive 'set' that persists into dot-probe processing. Specifically, the MDM would predict reduced sensitivity to dot-probes following low prevalence letter discrimination, reflecting the carryover of conservative identification thresholds from the primary task to the secondary task. The MDM framework emphasises decision-level mechanisms that should operate regardless of spatial location; therefore, this account predicts a main effect of prevalence on dot-probe detection but no interaction with eccentricity. This prediction is tested across Chapters 2–4 through examination of both accuracy and response times to dot-probes as a function of preceding letter discrimination prevalence.

The FVF framework (Hulleman & Olivers, 2017) offers an alternative account centred on spatial attention allocation. This framework proposes that difficult search tasks narrow the FVF, requiring more concentrated spatial sampling around fixation. Extended to sequential processing, the FVF framework predicts that low prevalence letter discrimination, being more difficult and requiring more focused attention, should result in a narrowed attentional window that persists into dot-probe processing. This account makes a unique prediction that distinguishes it from the MDM in that eccentricity should interact with prevalence effects. Dot-probes appearing at far eccentricities should show larger performance decrements following low prevalence letter discrimination compared to near eccentricities, as the narrowed FVF would particularly disadvantage more peripheral stimulus processing. As discussed earlier in this chapter, Menneer et al. (2017) provided preliminary evidence for prevalence-induced changes in spatial attention distribution, with fixations clustering differently under high versus low prevalence conditions. The current paradigm extends this by examining whether such spatial effects transfer to subsequent task performance. The interaction between prevalence and eccentricity is explicitly tested across all experiments in Chapters 2–4.

The resource depletion account, derived from SSM research (Adamo et al., 2021) and dual-task studies (Dell'Acqua et al., 2005; Isreal et al., 1980), suggests that detecting targets, particularly rare targets, consume limited cognitive resources. The attentional template account (Adamo et al., 2021) specifically proposes that maintaining target representations in working memory creates resource competition with subsequent visual processing. Applied to the current paradigm, this account predicts that low prevalence letter discrimination should deplete attentional resources more than high prevalence discrimination, leaving fewer resources available for subsequent dot-probe processing. Unlike the MDM and FVF accounts, the resource depletion framework makes a distinctive prediction: task difficulty manipulations in the letter discrimination task should interact with prevalence effects. If resource depletion drives sequential effects, more difficult letter discrimination should exacerbate the detrimental effects of low prevalence on dot-probe performance compared to easier discrimination. The interaction between prevalence and difficulty is explicitly tested in Chapter 3 (Experiments 3.1 and 3.2). Additionally, Chapter 4 tests this account by examining P3 amplitude as an electrophysiological index of available cognitive resources, with the prediction that low prevalence letter discrimination should reduce P3 amplitude to subsequent dot-probes, reflecting resource depletion.

The role of feedback in prevalence effects provides a test for distinguishing between implicit statistical learning and explicit strategic adaptation accounts. As discussed earlier in this chapter, feedback has been shown to moderate LPE magnitude in certain contexts, though its effects are inconsistent (Drew & Williams, 2017; Zhang et al., 2023). If the effects of prevalence in a primary task on performance in a secondary task reflect implicit statistical learning mechanisms that operate outside conscious control, then trial-by-trial feedback should have minimal impact on the transfer of prevalence effects to dot-probe performance. The statistical regularities would be encoded automatically, and explicit performance information would not prevent their influence on subsequent tasks. Conversely, if sequential effects result from deliberate strategic adjustments in attention allocation that participants could control if made aware of performance patterns, feedback should substantially reduce or eliminate the prevalence effects on dot-probe detection. Chapter 3 (Experiment 3.3) directly tests this distinction by comparing sequential task performance with and without trial-by-trial feedback in the letter discrimination task, enabling the differentiation between automatic and controlled processing accounts.

With these theoretical predictions established, the empirical chapters test these competing accounts through systematic manipulation of prevalence, task difficulty, feedback provision, and spatial eccentricity. The experiments reported in Chapter 2 provide foundational data on the basic prevalence effect in sequential tasks. The experiments in Chapter 3 explore whether (1) the provision of feedback for the letter discrimination task changes the findings reported in Chapter 2, (2) the effects of prevalence scale linearly, and (3) seeks to rule out a potential influence on the data reported in Chapter 2 of participants making pre-emptive eye movements away from fixation prior to the onset of the dot-probe. Chapter 4 explores the electrophysiological neural markers of the findings reported in Chapters 2 and 3, with particular focus on P3 amplitude as an index of attentional resource allocation. Finally, Chapter 5 provides a General Discussion in which all the findings are consolidated and the theoretical frameworks established in Chapter 1 are revisited considering the empirical evidence.

Chapter 2. The Effect of Target Prevalence on Performance in a Letter Discrimination and Dot-Probe Sequential Task.

Introduction

Chapter 1 established that low prevalence affects three key aspects of target detection and identification: threshold adjustment for identification, the allocation of spatial attention, and responses to subsequent visual events. These conclusions were drawn from a range of studies, however, in these studies the potential effects of prevalence were largely explored independently of each other. The experiments reported in Chapter 2 examine these effects and explore the relationship between them. Experiment 2.1 is guided by the notion that target prevalence is likely to influence the attentional capture of letters in a 2AFC letter discrimination task and explores how this will affect attentional resources available for subsequent visual processing of a dot-probe task.

Experiment 2.1 manipulates three key factors to test specific predictions about how prevalence might affect performance in a subsequent task. First, the manipulation of relative target prevalence in the 2AFC letter discrimination task tests whether letter identification is influenced by target prevalence. In this task, one of two possible target letters is presented such that both targets appear equally often (50%), or one target appears 90% of the time. The literature reviewed in Chapter 1 suggests that attention is most likely to be engaged by high prevalence targets such that they are reported more accurately than low prevalence targets.

Second, the difficulty of the 2AFC letter discrimination task is manipulated in two ways. The target letter is presented in isolation or within one or two virtual rings of eight distractor letters. The distractor letters were selected from a confusability matrix (Van der Heijden et al., 1984). Each entry in Van der Heijden et al.'s matrix gives the proportion of times that a very briefly presented letter (mean presentation time of 6.42 ms), positioned 2.75° visual angle from fixation, was identified as a specific letter identified as a response letter in a set of 1200 trials (see Appendix A for full details of the confusability matrix). Using Van der Heijden et al.'s confusability matrix, three sets of eight distractor letters were selected that varied in their discriminability from the targets. Thus, sets of distractor letters were created that are either easy, hard or at an intermediate level (medium) to discriminate from the targets. Varying the presence of distractor letters and the difficulty of discriminating them from targets allows the attentional demands associated with letter discrimination to be varied. The prediction is that increased attentional demands will be reflected in performance on the subsequent dot-probe task.

The dot-probe task is known to provide an index of spatial attention (MacLeod et al., 1986). In the present experiments, a dot-probe detection task is presented 105 ms (see Kim & Cave, 1995) after the offset of the 2AFC letter discrimination task. Critically, dot-probes appear in one of two virtual rings centred around fixation. The predictions are that both target prevalence and the presence of distractors in the 2AFC letter discrimination task will affect dot-probe detection. Specifically, low prevalence letter targets will draw attention such that dot-probe detection is reduced, and that this effect will be most striking for eccentrically presented dot-probes when letter discrimination is hard.

The hypotheses presented above are tested in two experiments. Experiment 2.1a was conducted at Liverpool Hope University, and Experiment 2.1b was conducted at Tianjin Normal University, China. This was due to restrictions placed on in-person testing at Liverpool Hope University during the COVID-19 pandemic, necessitating remote supervision of data collection at the Chinese site. Both experiments shared the same design and procedure.

Experiment 2.1

Method

Participants

Sample size was determined with an a priori power analysis using G*Power software (Erdfelder et al., 1996, Version 3.1.9.4) for the following parameters: power = .95, α = .05, β - 1 = .95, and a small to medium effect size of *d* = 0.40. This indicated a required sample size of 51 participants. Participant information for both experiments is detailed in Table 2.1. For Experiment 2.1a, the majority of participants were undergraduate Psychology students recruited via opportunistic sampling using the Liverpool Hope University participant recruitment scheme (SONA). All participants had self-reported normal or corrected-to-normal visual acuity. Participants took part in either the equal or unequal prevalence condition. Eligible students were awarded partial course credits for completing the experiment. Ethical approval was granted by the Liverpool Hope University Ethics Committee prior to commencement. All participants gave informed written consent before participating and were provided with debriefing information on completion of the experiment. For Experiment 2.1b, participants were recruited from Tianjin Normal University, China, using similar opportunistic sampling methods. All participants had self-reported normal or corrected-to-normal visual acuity and took part in either the equal or unequal prevalence condition. Ethical approval was granted prior to commencement, and all participants gave informed written consent before participating and were provided with debriefing information on completion of the experiment.

Table 2.1. *Participant information for Experiment 2.1a (UK) and Experiment 2.1b (China)*

	Experiment 2.1a (UK) Equal Prevalence Condition	**Experiment 2.1a (UK) Unequal Prevalence Condition**	**Experiment 2.1b (China) Equal Prevalence Condition**	**Experiment 2.1b (China) Unequal Prevalence Condition**
n	51	51	51	51
Age range (years)	18–48	18–66	18–27	18–25
Mean age (years)	22.76	26.84	20.78	20.39
SD	7.16	13.77	2.36	1.83
Sex	44 Female	42 Female	40 Female	41 Female

Note. SD = standard deviation.

Apparatus

The experiment was programmed in PsychoPy (Peirce, 2007; Peirce et al., 2019, Version 2021.2.1). Responses were recorded with a computer games controller. There were some differences between the apparatus used in Experiment 2.1a and 2.1b, which are detailed in Table 2.2. The screen size used to present the experiment was smaller in Experiment 2.1b, although the refresh rate remained the same. To mitigate the effects of differing screen sizes, participants were positioned closer to the screen in Experiment 2.1b, at approximately 60 cm, although viewing distances were not constrained in either experiment. All participants completed the experiment in an isolated experimental booth.

Table 2.2. *Details of experimental apparatus used in Experiment 2.1a (UK) and 2.1b (China)*

	Experiment 2.1a (UK)	**Experiment 2.1b (China)**
Distance from screen (cm)	Approx. 75	Approx. 60
Screen type	Samsung UHD TV	Asus VG248
Screen size	55-inch	24-inch
Resolution	3840 x 2160 pixels	1920 x 1080 pixels
Refresh rate	120 Hz	120 Hz
Games controller	PlayStation DualShock 4	Logitech Gamepad F310

Note. Screen types: Samsung UHD TV (Ultra High-Definition television); Asus VG248 (gaming monitor).

Stimuli

Unless presented in isolation (Single condition), the central target letter (either T or L) was surrounded by either one or two rings of eight upright continuous line black capital letters. Distractor letters were classified as Easy, Medium, or Hard, with letters from the same group arranged randomly. The Easy condition used the eight letters from the confusability matrix with the lowest combined confusability rates between both T and L, the Hard combination had the eight letters with the highest confusability, and the Medium condition had a confusability score part-way between the two (see Table 2.3 for details of letter combinations and confusability scores for each condition).

Table 2.3. *Letter combinations and confusability scores for Easy, Medium, and Hard letter discrimination conditions*

Condition	**Letter combination**	**Confusability score**
Easy	B, G, O, M, Q, X, D, S	0.053
Medium	H, Z, N, R, V, Z, A, K	0.097
Hard	I, J, L, T, F, U, P, Y	0.212

Note. Confusability scores represent the proportion of times letters within each condition were confused with the target letters T and L, based on van der Heijden et al. (1984).

The single virtual ring of distractor letters was 6.86° visual angle from fixation. The second virtual ring of distractor letters was 12.17° visual angle from fixation. Letters were scaled with increasing eccentricity per Anstis (1974) so that readability remained constant.

The central target letter subtended a visual angle of 0.76°, distractor letters subtended a visual angle of 1.14° (inner ring) and 1.91° (outer ring). Examples of stimuli are shown in Figure 2.1.

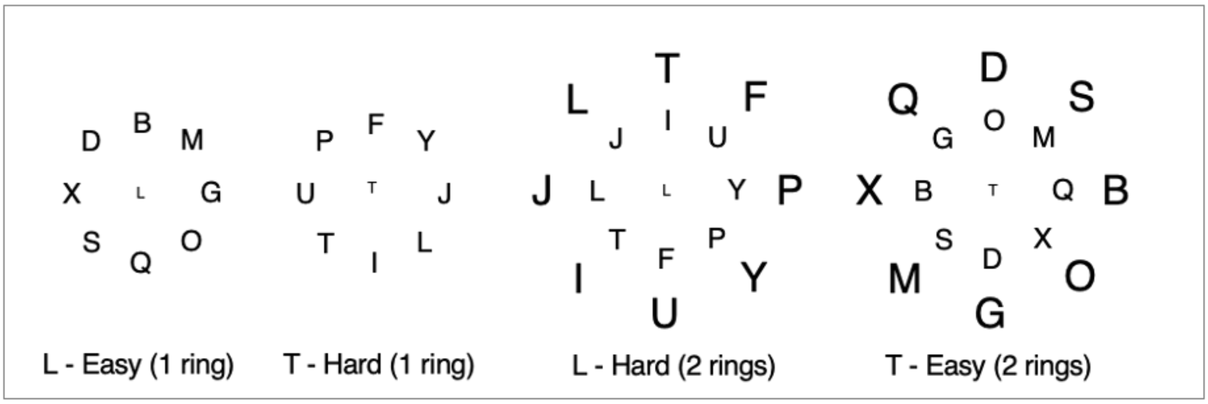


Figure 2.1. *Examples of stimuli used in the T/L letter discrimination task*

Note. Letters are scaled with increasing eccentricity so that they are equally readable.

Dot-probes were presented on 50% of trials at one of two eccentricities (Near or Far), the same distance from fixation as the two virtual rings of distractor letters. Probes appeared in one of eight possible positions, four equally spaced around each of the two virtual rings surrounding the central target letter. Probe positions were offset to coincide with spaces between distractor letters to minimise the effects of masking. Dot-probes appeared pseudo-randomly and with equal frequency in each of the eight locations.

Design and Procedure

The experiment had a mixed design with two within-subjects variables: Difficulty: four levels (Single, Easy, Medium, Hard) and Eccentricity: two levels (Near, Far); and one between-subjects variable: Prevalence: two levels (Equal, Unequal).

The experimental task consisted of two elements:

(1) Following the presentation of a centrally located fixation cross (400 ms duration), a central letter (either T or L) was briefly flashed on the screen (100 ms duration) either in isolation or surrounded by a single or double ring of distractor letters of varying confusability with the target letter. Participants were instructed to commit the target letter identity to memory and then prompted to respond with a button press to indicate which one of the central target letters was present (2AFC).

(2) Following a random 50% of trials, a dot-probe was briefly flashed on the screen (65 ms duration), 105 ms after the offset of the letter array. Participants were instructed to respond with a button press as soon as they saw a dot-probe appear. Participants were then prompted to respond with a button press to indicate which of the two target letters were present, as in the non-probe trials.

Unless presented in isolation, each target letter appeared with 1 or 2 rings of distractor letters for each difficulty level. Each condition appeared randomly three times per experimental block, totalling 126 trials per block, with a random 50% of trials followed by either a near or far dot-probe. The dot-probe appeared at each of the eight positions randomly and with equal frequency. Participants completed 20 random practice trials before the experiment commenced. There were three test blocks, totalling 378 trials per participant. Trial order was pseudo-randomised within each block for each participant. Participants were permitted to take short self-timed breaks between blocks. The course of a single trial is shown in Figure 2.2.

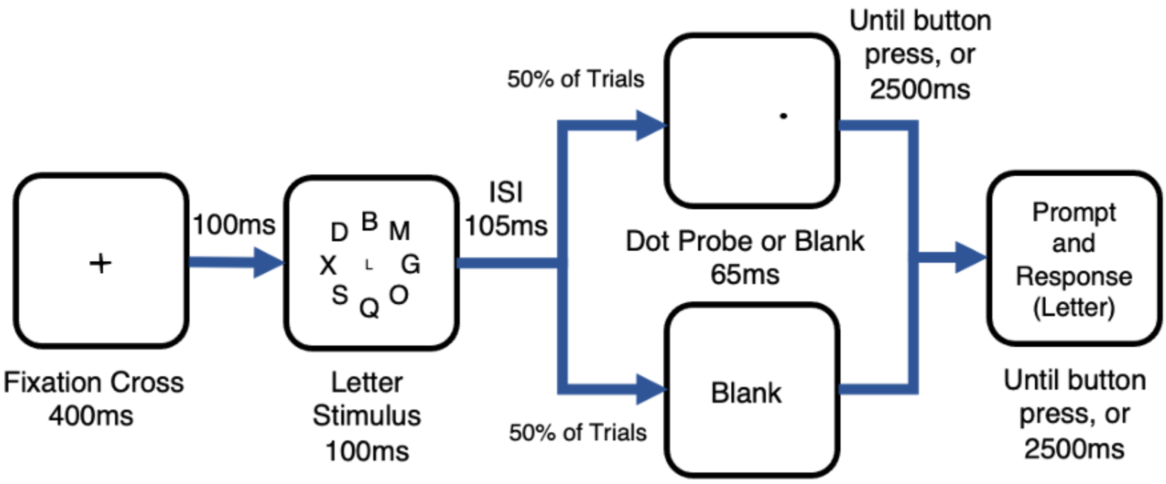


Figure 2.2. *Time course of a single experimental trial*

Note. Trial sequence showing fixation cross (400 ms duration), letter discrimination stimulus (100 ms duration), and dot-probe presentation on 50% of trials (65 ms duration).

Exclusion Criteria

Analysis was performed on data from participants with >90% accuracy in both the letter discrimination and dot-probe detection tasks to exclude data from participants who had not fully engaged with both elements. This excluded a total of 30 participants from Experiment 2.1a (6 from the equal prevalence condition and 24 from the unequal prevalence condition) and seven participants from Experiment 2.1b (all from the unequal prevalence condition). Following these exclusion criteria, the final sample consisted of 72 participants in Experiment 2.1a (n = 45 equal prevalence, n = 27 unequal prevalence) and 95 participants in Experiment 2.1b (n = 51 equal prevalence, n = 44 unequal prevalence). Response times under 200 ms and over 2500 ms were excluded from analysis to remove excessively fast or slow responses (see Whelan, 2008).

Of the 30 participants excluded from Experiment 2.1a, 24 (47.1% of the unequal prevalence condition; 15.7% of the total recruited UK sample) came from the unequal prevalence condition, suggesting that prevalence imbalance itself increased the likelihood of disengagement. To contextualise these exclusion rates, the proportion of excluded participants performing at or below chance level (50% accuracy) on the dot-probe task was calculated: 67% of excluded participants performed at or below chance, indicating genuine non-engagement. These high exclusion rates motivated procedural changes in subsequent experiments. In Experiments 3.1, 3.2, and 3.3, trial-by-trial audio feedback was introduced to promote sustained engagement, successfully reducing exclusion rates to 8.75%, 7.5%, and 13.2% respectively.

Analytic Strategy

Data were examined using Linear Mixed-Effect Model (LME) analyses of the relationship between target letter prevalence, letter discrimination difficulty, and dot-probe eccentricity using the lme4 package in R (Bates et al., 2014). To predict each measure at the trial level, Item (letter identity), Difficulty, and Eccentricity were entered as fixed effects, with intercepts for participant and trial entered as random effects, allowing values to vary between stimuli and participants. Model fitting began with a model containing the full set of two-way interactions which was iterated through different variants until reaching the best-fitting model (any models that failed to converge were excluded). Response times were log-transformed before analysis using standard LMEs. Accuracy data (measured as percentage correct and recorded as a binary value) were analysed using binomial generalised linear mixed-effect models (GLMEs).

Letter Discrimination Accuracy

Equal (50/50) and Unequal (90/10) prevalence conditions were examined separately. Factors examined in both prevalence conditions were Item (2: L_{50}, T_{50} [Equal], or L_{90}, T_{10} [Unequal]) x Difficulty (4: Single vs. Easy vs. Medium vs. Hard).

Dot-Probe Detection

Accuracy (along with non-parametric signal detection measures of sensitivity (A) and bias (logβ)) and response time data were used to explore performance in the dot-probe detection task. Accuracy was analysed using binomial generalised linear mixed modelling (GLME). Equal (50/50) and Unequal (90/10) prevalence conditions were examined separately. Factors examined in both prevalence conditions were Item (2: L_{50}, T_{50} [Equal], or L_{90}, T_{10} [Unequal]) x Difficulty (4: Single vs. Easy vs. Medium vs. Hard) x Eccentricity (2: Near vs. Far). Response times were analysed in the same way as the accuracy data using LME.

Non-parametric signal detection measures of Sensitivity (an individual's ability to differentiate between 'signal' and 'noise') and Bias (an individual's decision criteria, independent of sensitivity) were calculated for each participant from false alarm and hit rate data (see Zhang & Mueller, 2005, for the reasoning behind using A as the non-parametric measure of sensitivity instead of A'). Sensitivity and Bias were analysed using separate ANOVAs using the same factors and levels. To provide an integrated measure of performance that accounts for both speed and accuracy, Inverse Efficiency Scores (IES; Townsend & Ashby, 1978; Bruyer & Brysbaert, 2011; Vandierendonck, 2017; Liesefeld & Janczyk, 2019) were calculated. IES combines response time and accuracy into a single metric using the formula: IES = Mean RT / Proportion Correct. This approach addresses the speed-accuracy trade-off that can complicate the interpretation of RT and accuracy data when analysed separately. By dividing mean RT by the proportion of correct responses, IES provides a more comprehensive index of performance efficiency, where higher scores indicate poorer overall performance. Efficiency data were analysed in the same way as accuracy and response time data.

As detailed under Exclusion Criteria, 30 participants were removed from Experiment 2.1a (6 equal prevalence, 24 unequal prevalence) and 7 from Experiment 2.1b (all from unequal prevalence). The final samples were n = 72 (Experiment 2.1a) and n = 95 (Experiment 2.1b). Response times below 200 ms or above 2500 ms were excluded at the trial level. All analyses below are based on these cleaned datasets.

Results: Experiment 2.1a (UK)

Letter discrimination error rates were low throughout, confirming participants were engaged with the primary task. Under equal prevalence, discrimination accuracy was significantly affected by stimulus type: error rates were higher for letter arrays than for single letters. Under unequal prevalence, the classic low-prevalence effect emerged, with 10% targets producing substantially more errors than 90% targets. Letter arrays continued to produce higher error rates than single letters. There was no significant effect of dot-probe eccentricity in either prevalence condition (see Table 2.4).

Table 2.4. *Letter discrimination accuracy, Experiment 2.1a (UK)*

Prevalence condition	Effect	*b*	*SE*	*z*	*p*	Pattern
Equal	Difficulty	1.05	0.26	3.87	<.001	Higher errors for arrays than single letters
Unequal	Prevalence	0.38	3.78	7.14	<.001	Higher errors for 10% than 90% targets (classic low-prevalence effect)
Unequal	Difficulty	0.74	0.22	3.42	<.001	Higher errors for arrays than single letters

Dot-probe detection is reported across five measures — accuracy, response time, sensitivity (A), bias (logβ), and efficiency (IES). Under equal prevalence, dot-probe detection performance was primarily driven by letter stimulus type. Detection accuracy was significantly lower following letter arrays than single letters. Response times did not differ significantly across any factor. Sensitivity was lower following arrays, and response bias was more conservative. IES did not reach significance. Probe eccentricity was non-significant across all five measures (see Table 2.5).

The unequal prevalence condition produced a consistent pattern of impairment following low-prevalence targets. Detection accuracy was substantially worse following 10% targets than 90% targets. Response times were significantly slower. Sensitivity was reduced, response bias was more conservative and IES was significantly higher. Stimulus type also significantly affected accuracy and sensitivity. Probe eccentricity was non-significant across all measures (see Table 2.5). Full details of dot-probe detection performance are shown in Figure 2.3.

Table 2.5. *Dot-probe detection: summary of main effects across five dependent measures, Experiment 2.1a (UK)*

Effect	Accuracy	Response time	Sensitivity (A)	Bias (logβ)	IES
Equal Prevalence					
Difficulty	z = 3.87, p < .001*	n.s.	F = 5.00, p = .011*	F = 3.00, p = .037*	n.s.
Unequal Prevalence					
Prevalence	z = 0.49, p < .001*	t = 3.50, p < .001*	F = 10.00, p = .010*	F = 59.00, p < .001*	t = 6.56, p < .001*
Difficulty	z = 3.01, p < .001*	n.s.	F = 5.00, p = .017*	F = 11.00, p = .014*	n.s.

Note. * p < .05. IES = Inverse Efficiency Score, where higher scores indicate poorer performance. Eccentricity (near vs. far dot-probe) was non-significant across all five measures in both prevalence conditions.

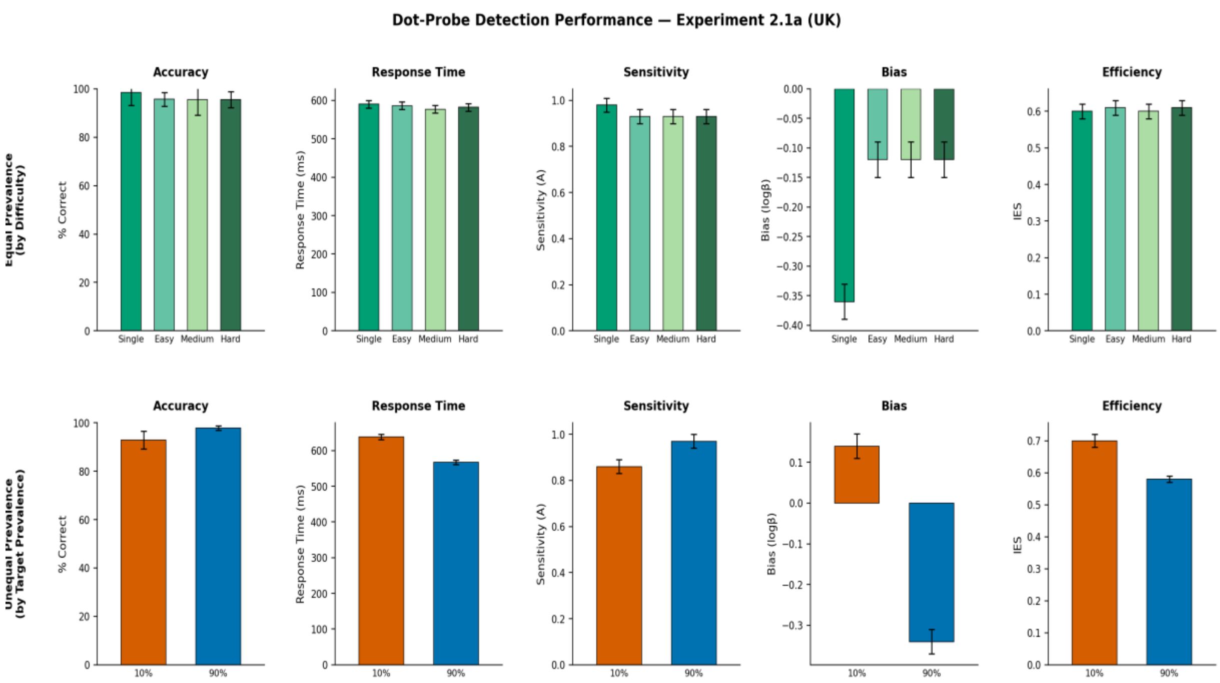


Figure 2.3. *Dot-probe detection performance in equal and unequal target prevalence conditions, Experiment 2.1a (UK): accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).*

Note. Bars show group means; error bars show ±SD. Equal-prevalence panels are broken down by letter discrimination difficulty; unequal-prevalence panels are broken down by target prevalence (10% vs. 90%).

Summary: Experiment 2.1a

In sum, Experiment 2.1a shows that low target prevalence (10%) impairs dot-probe detection on every measure examined: responses were slower, less accurate, less sensitive, more conservatively biased, and less efficient. Under equal prevalence, stimulus type was the main driver of performance costs, and probe eccentricity was non-significant throughout.

Results: Experiment 2.1b (China)

Experiment 2.1b used an identical task structure to Experiment 2.1a but was conducted with a Chinese sample, enabling a direct comparison. Results are reported in the same order: letter discrimination followed by dot-probe detection, examining equal and unequal prevalence conditions in turn.

Letter discrimination error rates were low across conditions, again confirming primary-task engagement. In contrast to Experiment 2.1a, discrimination errors under equal prevalence were more frequent for single letters than for letter arrays. Under unequal prevalence, the low-prevalence effect was replicated with 10% prevalence targets producing more errors than 90% targets. The reversed display-type pattern was maintained, with single letters producing higher error rates than letter arrays. No further effects or interactions reached significance (see Table 2.6).

Table 2.6. *Letter discrimination accuracy, Experiment 2.1b (China)*

Prevalence condition	Effect	*b*	*SE*	*z*	*p*	Pattern
Equal	Difficulty	0.86	0.23	3.74	<.001	Higher errors for single letters than arrays (reversed vs. 2.1a)
Unequal	Prevalence	0.51	3.20	2.98	<.001	Higher errors for 10% than 90% targets
Unequal	Difficulty	1.42	0.26	4.12	<.001	Higher errors for single letters than arrays (reversed vs. 2.1a)

Under equal prevalence, dot-probe detection accuracy showed no significant effects of any factor, suggesting near-ceiling performance. However, response times were significantly faster following letter arrays than single letters. Sensitivity was reduced following arrays, bias was more conservative, and IES was higher following single letters. Probe eccentricity was non-significant across all measures (see Table 2.7).

The unequal prevalence condition replicated Experiment 2.1a across all five dependent variables. Accuracy was significantly lower following 10% targets. Response times were significantly slower. Sensitivity was reduced, response bias was more conservative, and IES was significantly higher. Stimulus type also significantly affected accuracy and response time. Probe eccentricity was non-significant across all measures (see Table 2.7). Full details of dot-probe detection performance are shown in Figure 2.4.

Table 2.7. *Dot-probe detection: summary of main effects across five dependent measures, Experiment 2.1b (China)*

Effect	Accuracy	Response time	Sensitivity (A)	Bias (logβ)	IES
Equal Prevalence					
Difficulty	n.s.	*t* = −3.76, *p* < .001*	*F* = 4.00, *p* = .012*	*F* = 4.00, *p* = .010*	*t* = −2.00, *p* = .047*
Unequal Prevalence					
Prevalence	*z* = 3.42, *p* < .001*	*t* = −9.06, *p* < .001*	*F* = 7.00, *p* = .010*	*F* = 22.00, *p* < .001*	*t* = 8.76, *p* < .001*
Difficulty	*z* = 2.23, *p* < .001*	*t* = -3.72, *p* = .014*	*F* = 3.00, *p* = .039*	*F* = 9.00, *p* < .001*	n.s.

Note. * *p* < .05. IES = Inverse Efficiency Score, where higher scores indicate poorer performance. Eccentricity was non-significant across all five measures in both prevalence conditions.

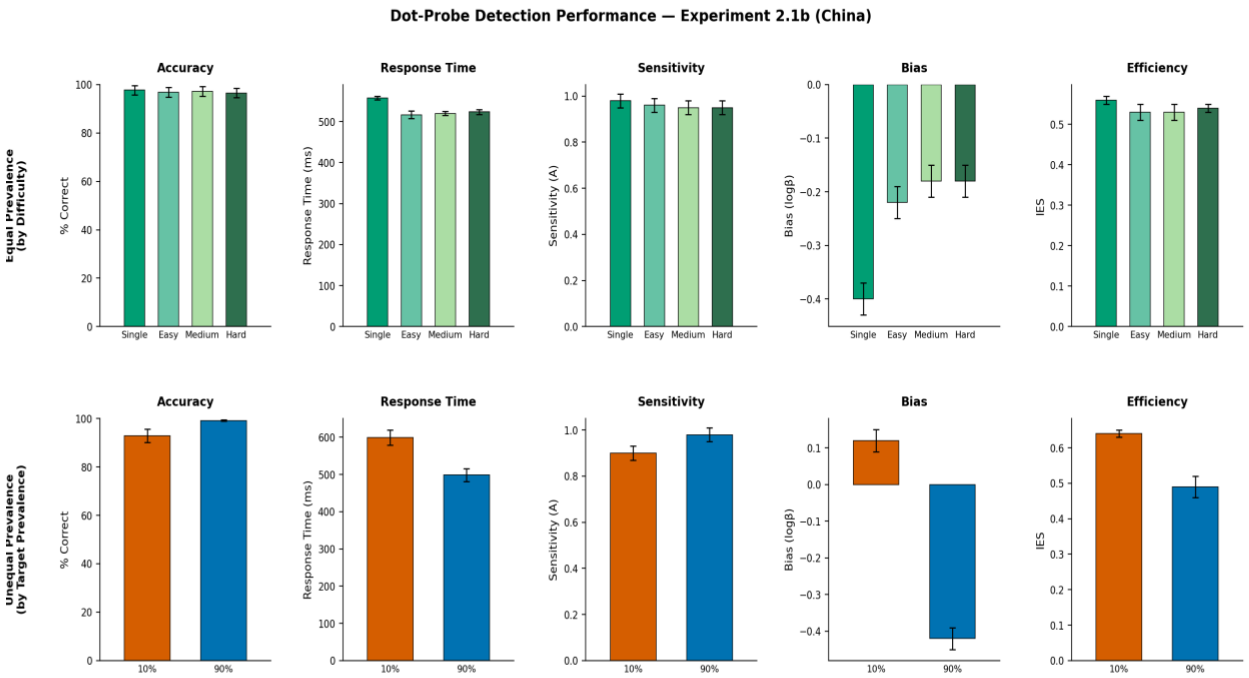


Figure 2.4. *Dot-probe detection performance in equal and unequal target prevalence conditions, Experiment 2.1b (China): accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).*

Note. Bars show group means; error bars show ±SD. Equal-prevalence panels are broken down by letter discrimination difficulty; unequal-prevalence panels are broken down by target prevalence (10% vs. 90%).

Summary: Experiment 2.1b

Experiment 2.1b closely replicated Experiment 2.1a with a Chinese sample. Under unequal prevalence, low-prevalence targets impaired dot-probe detection across all five measures. Under equal prevalence, performance was primarily determined by display type, though the RT direction was reversed relative to Experiment 2.1a. Probe eccentricity was non-significant throughout both experiments.

Combined Summary: Experiments 2.1a and 2.1b

Across both experiments the pattern of results was strikingly consistent. Under equal prevalence, letter display difficulty was the primary driver of dot-probe performance. Under unequal prevalence, a robust low-prevalence effect emerged across all five dependent measures — accuracy, response time, sensitivity (A), bias (logβ), and efficiency (IES) — in both the UK and Chinese samples. The absence of any significant eccentricity effects or prevalence × eccentricity interactions in either experiment indicates that the attentional consequences of low target prevalence are not spatially localised to probe position but reflect a generalised disruption of detection capacity. This combined pattern is the foundation for Chapter 3, which tests how robust this cost is to feedback, gaze constraints, and graded prevalence.

Discussion

Chapter 1 established that prevalence affects target detection and identification through three key mechanisms: decision threshold adjustment, changes in spatial attention, and response behaviour adjustments. However, it was unclear whether these prevalence-induced cognitive adjustments extend beyond immediate task boundaries to influence subsequent visual processing. Experiment 2.1 provides evidence confirming the central proposition outlined in Chapter 1 that target prevalence in a primary task affects performance in a subsequent task.

Experiment 2.1 used a sequential task paradigm consisting of a letter discrimination task followed closely by a dot-probe detection task. Three key factors were manipulated: relative target letter prevalence, task difficulty and dot-probe eccentricity. The results show that the presentation of low prevalence targets in the letter discrimination task led to poorer performance in the dot-probe task. This finding held across multiple measures: slower response times, reduced accuracy, lower sensitivity, and more conservative decision criteria. These effects were replicated across both experimental sites and remained consistent regardless of task difficulty or probe eccentricity.

Regarding letter discrimination difficulty, in both equal and unequal prevalence conditions, dot-probe detection was more accurate, achieved with greater sensitivity and a more liberal bias, following single letters than letter arrays. However, there was no effect of letter discrimination difficulty beyond this, with levels of letter confusability within the sets of distractor letters not affecting performance on the dot-probe task. Likewise, the eccentricity of dot-probes did not affect their detection.

Overall, the pattern of results is consistent with attention being drawn to low prevalence targets such that the processing of subsequent visual events is impaired. However, other than an influence of the presence of distractor letters on dot-probe detection, the results showed the main finding to be unaffected by more nuanced efforts to manipulate task difficulty. Moreover, the effects of task difficulty on letter discrimination did not interact with target prevalence. Importantly, the absence of any effects of probe eccentricity, or interactions between prevalence and eccentricity, indicate that the impairment in subsequent visual processing was not spatially localised. As such, although there is clear evidence in the results of Experiment 2.1 that target prevalence affects subsequent visual processing, there is no evidence that this occurs through a mechanism of spatially specific attentional capture. Rather, the findings suggest that low prevalence targets influence subsequent processing through a more general attentional or decision-related mechanism that operates independently of spatial location.

There are however, two key limitations that might affect the interpretation and generalisability of the findings reported in Experiment 2.1. The exclusion rate due to accuracy criteria was substantial in the UK sample, where 30 participants were removed (six from the equal prevalence condition and 24 from the unequal prevalence condition) compared to seven participants removed from the Chinese sample (all from the unequal prevalence condition). Despite the broader age range in Experiment 2.1a (18–48 years) compared to Experiment 2.1b (18–27 years), the pattern of exclusions is unlikely to be explained by age differences, as the majority of excluded participants were undergraduates within the typical student age range. Rather, this raises concerns about the robustness of the observed effects, particularly for the unequal prevalence condition, and suggests potential issues with participant engagement that may limit generalisability.

Additionally, the use of different apparatus between experimental sites introduces potential confounds that could affect replication. Although comparable visual angles were achieved through adjusted viewing distances, the differences in testing environments may have contributed to the observed differences in results and therefore limit confidence in the robustness of findings across contexts. The studies presented in Chapter 3 seek to address these potential shortcomings in the design and implementation of Experiment 2.1. Additionally, consistent apparatus will be used across all testing sessions to ensure methodological consistency.

Experiment 3.1 replicates Experiment 2.1 but with the addition of trial-by-trial audio feedback for the 2AFC letter discrimination task to help participants maintain focus. Experiment 3.2 uses eye tracking to address a potential concern with Experiment 3.1 that participants could be making pre-emptive eye movements away from fixation in anticipation of a dot-probe appearing. Experiment 3.3 explores whether the sequential prevalence effects observed in Experiment 2.1 scale proportionally with the magnitude of prevalence manipulation, examining whether the observed effects of prevalence on a subsequent task reflect graded responses to statistical regularities or categorical responses to the presence versus absence of prevalence imbalance.

Chapter 3. Investigating the Persistence of Low Prevalence Effects on a Subsequent Task

Introduction

Experiment 2.1 established a baseline for the effects of equal vs. unequal prevalence in a letter discrimination task on performance in a subsequent dot-probe detection task. The results showed that the effects of low prevalence propagate from the letter discrimination task to the subsequent dot-probe detection task, demonstrating that prevalence-induced attentional biases extend beyond the immediate task in which they are established. However, there were potential limitations which could limit the generalisability of these findings. The experiments presented in Chapter 3 seek to address these potential shortcomings and ensure that the effects reported in Chapter 2 are not influenced by the presence of artifacts in the data.

Chapter 3 reports three experiments investigating the persistence and scalability of the prevalence effects identified in Chapter 2, using the same sequential task paradigm consisting of a letter discrimination task closely followed by a dot-probe detection task. Experiment 3.1 replicates Experiment 2.1 with the addition of trial-by-trial audio feedback on performance in the letter discrimination task. This measure seeks to encourage participants to remain focussed on the task, as participant engagement was a potential limitation identified in Experiment 2.1. In addition to focussing attention, previous research has shown that feedback can moderate prevalence effects by shifting decision criteria back to a neutral state (Horowitz, 2017). It was therefore predicted that trial-by-trial feedback would partially modulate the effects of low prevalence on dot-probe detection observed in Experiment 2.1 by improving task engagement and recalibrating response criteria, while leaving intact any automatic attentional capture triggered by rare targets.

Experiment 3.2 addresses a methodological concern arising from Experiment 3.1 that participants might seek to gain an advantage on the dot-probe detection task by making pre-emptive eye movements away from fixation in anticipation of the appearance of a dot-probe, which could confound the interpretation of results. Such anticipatory eye movements are a well-documented concern in spatial attention paradigms (Jonides, 1981; Klein, 2000; Posner, 1980), where they can inflate or obscure genuine effects of covert attentional allocation. In dot-probe paradigms specifically, participants may learn the temporal predictability of probe onset and strategically move their eyes toward likely probe locations (Koster et al., 2004; Mogg et al., 2000), potentially masking true differences in attentional deployment across conditions. Experiment 3.2 replicates the feedback conditions from Experiment 3.1 but incorporates eye tracking to monitor participants' eye movements as they complete the task. Trials containing eye movements away from fixation prior to the onset of dot-probes will be excluded from analysis, ensuring that the observed effects reflect genuine covert attentional allocation rather than overt shifts in attention.

Finally in this chapter, Experiment 3.3 investigates whether the effects of low prevalence on dot-probe detection scale proportionally with the magnitude of prevalence imbalance, with greater prevalence imbalance in the letter discrimination task producing stronger effects on performance in the dot-probe detection task. Experiment 3.3 employs a blocked design with progressively increasing prevalence imbalance (50/50, 70/30, and 90/10 ratios). This design tests whether the relationship between prevalence imbalance and sequential effects is linear or exhibits threshold effects, examining whether the effects of prevalence on a subsequent task reflect graded responses to statistical regularities or categorical responses to the presence versus absence of prevalence imbalance. It is predicted that the blocked design will moderate prevalence effects on dot-probe detection, with participants' performance improving as they progress through the blocks of increasing prevalence imbalance.

Experiment 3.1

Experiment 3.1 acts as a replication study of Experiment 2.1 with the addition of trial-by-trial audio feedback on performance in the letter discrimination task to encourage participants to remain engaged. Experiment 3.1 uses the same experimental design and stimuli as Experiment 2.1 with the exception of the removal of the Medium difficulty condition as this showed the smallest change under different manipulations in Experiment 2.1.

Method

Participants

An a priori power analysis using G*Power software (Erdfelder et al., 1996, Version 3.1.9.4) was used to calculate the required sample size to have sufficient power to detect a small to medium effect size of d = 0.40. The following parameters were used: power = .95, α = .05, β - 1 = .95, which indicated a required sample size of 72 participants. 80 participants completed the experiment to account for possible withdrawals; 57 of which were female (age range = 18–42 years, M = 24.63, SD = 6.42). All participants self-reported having normal or corrected-to-normal visual acuity. For all experiments reported in this chapter, the majority of participants were undergraduate Psychology students recruited via opportunistic sampling using the Liverpool Hope University participant recruitment scheme (SONA). Eligible students were awarded partial course credit for completing the experiment. Ethical approval was granted by the Liverpool Hope University Ethics Committee prior to commencement. All participants gave informed written consent before participating and were provided with debriefing information on completion of the experiment. None of the participants had taken part in Experiment 2.1.

Apparatus

The experiment was programmed in PsychoPy (Peirce, 2007; Peirce et al., 2019, Version 2022.2.4), with additional custom code written in Python. The experiment was presented on a 21.5-inch Dell P2219H monitor (resolution: 1920 x 1080 pixels, refresh rate: 60 Hz). Participants viewed the screen from approximately 60 cm, but this was not constrained. Responses were recorded by keyboard button presses which were counterbalanced for 50% of participants.

Design and Procedure

Experiment 3.1 had a mixed design with two within-subjects variables: Difficulty: 3 levels (Single, Easy, Hard) and Eccentricity: 2 levels (Near, Far); and two between-subjects variables: Prevalence: 2 levels (Equal, Unequal) and Feedback: 2 levels (Feedback, No Feedback).

Participants were pseudo-randomly allocated to one of four experimental groups (20 per group). Group 1 completed the experiment at equal prevalence but received no feedback on their performance. Group 2 completed the same experiment but received audio feedback following every trial. Group 3 completed the experiment at unequal prevalence with no feedback and Group 4 completed the same experiment with feedback. Feedback consisted of a high 'ding' sound (1000 Hz) being played (100 ms duration) following correct letter discrimination, and a corresponding low 'buzzer' sound (300 Hz) being played (100 ms duration) for incorrect letter discrimination. Sounds were selected from an online sound effect library. Feedback was given on each trial immediately following target letter selection, with participants in the feedback groups informed that they would receive feedback on their performance prior to beginning the experiment.

Participants completed the experiment in an isolated experimental booth with the experimenter sitting out of view to monitor compliance with the task. Participants completed 150 trials per block, at either equal or unequal target letter prevalence. Following a practice block consisting of 20 random trials, participants completed two test blocks, totalling 300 trials per participant. The trial order was pseudo-randomised within blocks for each participant. Participants were permitted to take a short self-timed break between blocks.

Exclusion Criteria

Response time analyses were conducted on correct responses only; trials on which an incorrect response was made to either the letter discrimination or dot-probe detection task were excluded from the corresponding RT calculations. This ensured that RT data reflected the speed of accurate responding rather than being contaminated by error trials, which may reflect qualitatively different processing.

Analysis was performed on data from participants with greater than 90% accuracy in both tasks to exclude data from participants who had not fully engaged with both elements of the task. This resulted in the removal of three participants from Group 1 (equal prevalence, no feedback; 15.0% of group), two from Group 2 (equal prevalence, feedback; 10.0%), zero from Group 3 (unequal prevalence, no feedback), and two from Group 4 (unequal prevalence, feedback; 10.0%), yielding a total of seven excluded participants (8.75% of the recruited sample). Response times below 200 ms or above 2500 ms were removed to remove excessively fast or slow responses (see Whelan, 2008), resulting in exclusion of 4.7% of trials.

Analytic Strategy

Data were examined using Linear Mixed-Effect Model (LME) analyses of the relationship between target letter prevalence, letter discrimination difficulty, feedback and dot-probe eccentricity using the lme4 package in R (Bates et al., 2014). To predict each measure at the trial level, Item (letter identity), Difficulty, Feedback and Eccentricity were entered as fixed effects, with intercepts for participant and trial entered as random effects, allowing values to vary between stimuli and participants. Equal (50/50) and Unequal (90/10) prevalence conditions were examined separately. Factors examined in both prevalence conditions were Item (2: L_{50}, T_{50} [Equal] or L_{90}, T_{10} [Unequal]) x Difficulty (3: Single vs. Easy vs. Hard) x Feedback (2: Feedback vs. No-Feedback) x Eccentricity (2: Near vs. Far).

Model fitting began with a model containing the full set of two-way interactions which was iterated through different variants until reaching the best-fitting model (any models that failed to converge were excluded). Visual inspection of residual plots did not reveal any obvious deviations from normality. Response times were log-transformed before analysis using standard LMEs. Accuracy (measured as percentage correct and recorded as a binary value) was analysed using binomial generalised linear mixed-effect models (GLMEs). Nonparametric signal detection measures of sensitivity (A) and bias (logβ) were calculated for each participant from false alarm and hit rate data and analysed using separate ANOVAs using the same factors and levels.

Results

Feedback made participants more accurate on both tasks, but it did not protect dot-probe detection from the cost of low prevalence. Under unequal prevalence, detection was worse following 10% targets than 90% targets on every measure — accuracy, response time, sensitivity, bias, and efficiency — regardless of whether feedback was given. Feedback's benefit manifested instead as a moderator of task difficulty: with feedback, sensitivity, bias, and efficiency became more finely tuned to how hard the preceding letter discrimination had been, an effect that was absent without feedback.

Letter discrimination accuracy followed the expected pattern: arrays produced more errors than single letters, feedback reduced errors overall, and, under unequal prevalence, 10% targets produced more errors than 90% targets (see Table 3.2). The prevalence cost on discrimination was itself smaller with feedback than without it.

Table 3.1. *Letter discrimination accuracy: significant and non-significant effects, Experiment 3.1*

Prevalence condition	Effect	*b*	*SE*	*z*	*p*	Pattern
Equal	Difficulty	0.05	0.02	2.50	.012	Higher errors for arrays than single letters
Equal	Feedback	−0.18	0.08	−2.25	.024	Lower errors with feedback
Equal	Prevalence	−0.03	0.12	−0.25	.803	n.s.
Equal	Feedback × Difficulty	−0.10	0.08	−1.25	.211	n.s.
Unequal	Prevalence	−0.55	0.15	−3.67	<.001	Higher errors for 10% than 90% targets
Unequal	Difficulty	−0.03	0.01	−2.08	.038	Higher errors for arrays than single letters
Unequal	Feedback	−0.87	0.18	−4.83	<.001	Lower errors with feedback
Unequal	Feedback × Item	0.52	0.21	2.48	.013	Prevalence cost larger without feedback
Unequal	Feedback × Difficulty	−0.01	0.02	−0.50	.617	n.s.

Turning to the dot-probe task, Table 3.2 summarises performance on the dot-probe task across all five dependent measures, for both equal and unequal prevalence conditions. The pattern is clearest under unequal prevalence: rare (10%) targets impaired accuracy, speed, sensitivity, bias, and efficiency alike, and this cost was unaffected by feedback. Under equal prevalence, prevalence itself had no effect on performance; instead, performance tracked the difficulty of the preceding discrimination. Critically, this difficulty effect on sensitivity, bias, and efficiency only emerged when feedback was present, reflected in a significant Feedback × Difficulty interaction. Figure 3.1 shows dot-probe detection performance in equal and unequal target prevalence conditions across five measures: accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).

Table 3.2. *Dot-probe detection: summary of main effects across five dependent measures, Experiment 3.1*

Effect	Accuracy	Response time	Sensitivity (A)	Bias (logβ)	IES
Equal Prevalence					
Prevalence	z = 0.84, p = .401	t = 0.67, p = .503	F = 1.79, p = .190	F = 1.01, p = .322	t = 0.63, p = .531
Difficulty	z = −2.38, p = .017*	t = 1.00, p = .318	F = 3.89, p = .031*	F = 22.35, p < .001*	t = 2.00, p = .048*
Feedback	z = −0.83, p = .406	t = −0.67, p = .503	F = 0.82, p = .372	F = 0.58, p = .452	t = −0.87, p = .387
Eccentricity	z = −0.03, p = .976	t = 0.50, p = .617	F = 1.24, p = .274	F = 1.71, p = .200	t = 0.50, p = .619
Feedback × Difficulty	n.s.	n.s.	F = 4.12, p = .026*	F = 19.87, p < .001*	t = 2.03, p = .045*
Unequal Prevalence					
Prevalence	z = 2.45, p = .014*	t = −6.88, p < .001*	F = 6.89, p = .013*	F = 5.12, p = .030*	t = 5.67, p < .001*
Difficulty	z = 0.91, p = .362	t = −2.92, p = .004*	F = 0.70, p = .503	F = 1.12, p = .337	t = 0.03, p = .976
Feedback	z = −1.87, p = .061	t = −1.25, p = .214	F = 4.37, p = .044*	F = 2.14, p = .152	t = −2.22, p = .031*
Eccentricity	z = −0.83, p = .414	t = 0.88, p = .381	F = 0.57, p = .455	F = 0.51, p = .480	t = 0.40, p = .690
Feedback × Item	z = 1.71, p = .087	n.s.	F = 1.48, p = .232	n.s.	t = 2.50, p = .015*
Feedback × Difficulty	n.s.	t = 3.61, p < .001*	n.s.	n.s.	n.s.

Note. * p < .05. IES = Inverse Efficiency Score, where higher scores indicate poorer performance.

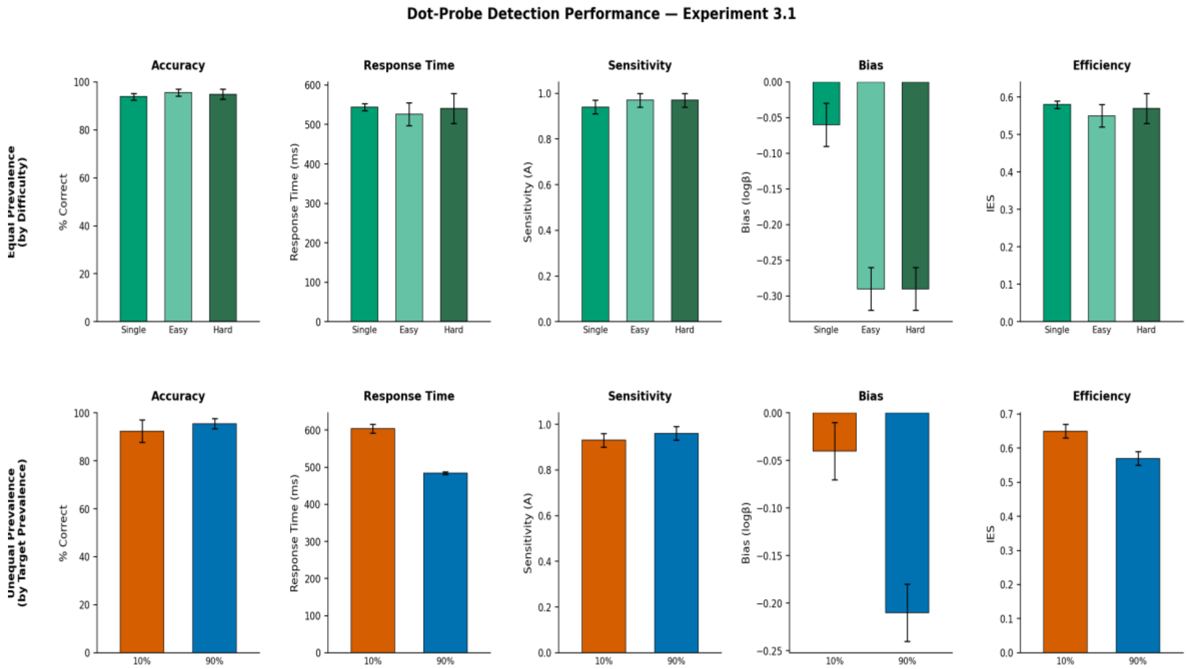


Figure 3.1. *Dot-probe detection performance in equal and unequal target prevalence conditions (Experiment 3.1): accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).*

Note. Bars show group means; error bars show ±SD. Equal-prevalence panels are broken down by letter discrimination difficulty; unequal-prevalence panels are broken down by target prevalence (10% vs. 90%). Feedback did not change the direction of any of these effects (see text and Table 3.2) and is not shown as a separate breakdown here.

In sum, in the equal prevalence condition, feedback did not improve overall dot-probe detection performance. However, feedback did modulate the effect of letter discrimination difficulty on dot-probe sensitivity and bias, specifically by enhancing the advantage for easy trials while amplifying the cost for hard trials. When feedback was provided, participants showed greater sensitivity following easy discriminations and more conservative response bias following hard discriminations, suggesting that feedback heightened participants' awareness of task demands and led to more differentiated response patterns based on discrimination difficulty. Feedback on the letter discrimination task did not, however, reduce the effect of low prevalence on dot-probe detection accuracy, sensitivity, or bias. Importantly, the effect of difficulty on dot-probe detection only emerged when feedback was provided. In the unequal prevalence condition, dot-probe detection was worse following low prevalence targets than high prevalence targets and following the presentation of only the target letter than following letter arrays. In sum, providing feedback on the letter discrimination task improved dot-probe detection but did not change the effect of letter prevalence on dot-probe detection.

Discussion

Experiment 3.1 examined whether the effects of manipulating prevalence in a letter discrimination task on performance in a dot-probe detection task observed in Experiment 2.1 persist when participants receive trial-by-trial audio feedback on their letter discrimination performance. The central question was whether feedback would reduce the effects of low prevalence on subsequent dot-probe detection.

Feedback did improve performance in the letter discrimination and dot-probe detection tasks. However, the effects of low prevalence on letter discrimination and dot-probe detection persisted despite the provision of feedback. In the unequal prevalence condition, dot-probe detection was worse following low prevalence targets compared to high prevalence targets across all measures, with higher error rates, slower response times, reduced sensitivity, and more conservative bias, regardless of whether participants received feedback or not. These results replicated the findings from Experiment 2.1, demonstrating the robustness of the effects of low prevalence on subsequent task performance.

In summary, Experiment 3.1 demonstrates that providing trial-by-trial feedback improves performance in both the letter discrimination and dot-probe tasks. However, whilst the provision of feedback reduces the magnitude of the effect of prevalence in both tasks, it does not eliminate it. In conclusion, the effects of low prevalence on subsequent task performance identified in the experiments reported in Chapter 2 are not eliminated by trial-by-trial feedback.

The persistence of prevalence effects despite feedback suggests several possible explanations. First, the attentional capture triggered by rare targets may operate at a relatively automatic level that occurs too rapidly to be modulated by feedback-driven strategic adjustments (Theeuwes, 2010; Yantis & Egeth, 1999). Second, feedback may primarily influence decisional processes and response strategies rather than the early attentional allocation mechanisms that underlie prevalence effects (Wolfe et al., 2007). Trial-by-trial feedback informs participants about their accuracy but may not provide sufficient information to recalibrate statistical expectations about target frequency. Third, statistical learning about prevalence rates accumulates over many trials (Chun & Jiang, 1998; Turk-Browne et al., 2009) and may create attentional biases that cannot be easily overridden by trial-by-trial performance feedback alone. The gradual accumulation of statistical regularities may establish expectations that persist even when participants are made aware of individual errors. Finally, the temporal proximity of the letter discrimination and dot-probe tasks may leave insufficient time for feedback-driven strategic adjustments to influence subsequent task performance, particularly if the attentional capture effects occur within the first few hundred milliseconds following rare target detection (Horstmann, 2002).

Experiment 3.2

Experiment 3.2 explores whether the effects of feedback seen in Experiment 3.1 are affected by pre-emptive eye movements away from fixation prior to the appearance of dot-probes. Experiment 3.2 replicates the feedback conditions from Experiment 3.1 with the addition of eye tracking to monitor eye movements.

Method

Participants

40 participants took part in the experiment (31 were female, age range 18–45 years, *M* = 22.43, *SD* = 5.84), replicating the sample size from the feedback conditions in Experiment 3.1. Participants were pseudo-randomly assigned to complete either the equal or unequal prevalence condition (20 per group). All participants self-reported having normal or corrected-to-normal visual acuity. None of the participants had taken part in Experiment 3.1.

Apparatus

The experiment was programmed in PsychoPy (Peirce, 2007; Peirce et al., 2019, Version 2022.2.4) using builder eye tracking components, with additional custom code written in Python. Eye movements were recorded with a desktop-mounted EyeLink 1000 Plus eye tracker. Eye movements were recorded at 1000 Hz. Participants' eye movements were calibrated using a nine-point calibration procedure and accepted only when the average calibration error was less than 0.5° visual angle, and none of the points had a calibration error of more than 1° visual angle. Calibration was re-checked following a break between blocks and was repeated mid-block if the drift correction indicated that gaze had shifted by more than 1° visual angle from the central fixation point. Viewing was binocular, though only the right eye was tracked. The experiment was presented on a Benq 23-inch monitor (resolution: 1920 x 1080 pixels, refresh rate: 60 Hz). Responses were recorded using keyboard button presses which were counterbalanced for 50% of participants. Participants viewed the monitor at 57 cm from a stabilised chin rest in a dimly lit room with the experimenter sitting out of view to monitor compliance with the task.

Design and Procedure

Prevalence: two levels (Equal, Unequal) was the only between-subjects variable. There were two within-subject variables: Difficulty: 3 levels (Single, Easy, Hard), and Eccentricity: 2 levels (Near, Far).

After a practice session consisting of 20 random trials, participants completed two experimental blocks of 150 trials at either equal or unequal target letter prevalence. Trial order was pseudo-randomised within each block and participants were permitted to take a short self-timed break between blocks. Feedback was provided to all participants and was identical to the feedback provided in the feedback conditions of Experiment 3.1.

Exclusion Criteria and Analytic Strategy

The exclusion criteria were the same as in Experiment 3.1. This resulted in the removal of data from one participant in the equal prevalence group, and two participants in the unequal prevalence group. Response time parameters resulted in 3.8% of trials being removed from the dataset. A total of 3.3% of trials were excluded from analysis as they contained eye movements away from fixation following the offset of the fixation cross. Default EyeLink parameters were used to classify fixations, with trials excluded if participants made an eye movement away from the central fixation cross following fixation offset and prior to dot-probe onset. Specifically, a trial was excluded if gaze deviated more than 1.5° visual angle from fixation during this period, consistent with recommendations for brief-stimulus eye-tracking paradigms (Godwin et al., 2021). Trials in which the eye tracker failed to record a valid gaze sample for more than 50% of the fixation period were also excluded to ensure data quality. Behavioural data were analysed in the same way as in Experiment 3.1.

Results

Experiment 3.2 addressed a specific alternative explanation for Experiment 3.1: that participants were looking ahead to likely probe locations while the letters were still on screen, rather than genuinely being affected by target prevalence. Removing this possibility left the pattern unchanged. Under unequal prevalence, 10% targets again produced worse dot-probe accuracy, slower responses, lower sensitivity, and more conservative bias than 90% targets; under equal prevalence, performance was again driven by discrimination difficulty. Statistically, the two experiments did not differ on any measure (all interaction p values > .286; full contrasts in Appendix B). This rules out anticipatory eye movements as the source of the prevalence cost and confirms that the effect is robust to this methodological change.

In short, Experiment 3.2 fully replicates Experiment 3.1 while ruling out anticipatory gaze as an explanation: the cost of low prevalence on a subsequent, unrelated task is not an artefact of where participants were looking. Details of letter discrimination and dot-probe statistical effects are shown in Tables 3.3 and 3.4. Figure 3.2 shows dot-probe detection performance in equal and unequal target prevalence conditions across five measures: accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).

Table 3.3. *Letter discrimination accuracy: significant effects, Experiment 3.2*

Prevalence condition	**Effect**	***b***	***SE***	***z***	***p***	**Pattern**
Equal	Difficulty	0.04	0.02	2.03	.045	Higher errors for arrays than single letters
Unequal	Prevalence	−0.25	0.09	−2.78	.010	Higher errors for 10% than 90% targets
Unequal	Difficulty	0.18	0.07	2.54	.013	Higher errors for arrays than single letters

Table 3.4. *Dot-probe detection: summary of main effects across five dependent measures, Experiment 3.2*

Effect	Accuracy	Response time	Sensitivity (A)	Bias (logβ)	IES
Equal Prevalence					
Prevalence	$z = 0.33$, $p = .753$	$t = 0.83$, $p = .428$	$F = 1.84$, $p = .193$	$F = 0.04$, $p = .833$	$t = -0.13$, $p = .897$
Difficulty	$z = 2.49$, $p = .011$*	$t = -0.21$, $p = .180$	$F = 3.32$, $p = .043$*	$F = 4.34$, $p = .014$*	$t = 3.75$, $p < .001$*
Eccentricity	$z = 1.74$, $p = .096$	$t = 1.67$, $p = .262$	$F = 0.17$, $p = .687$	$F = 1.47$, $p = .231$	$t = 0.33$, $p = .741$
Unequal Prevalence					
Prevalence	$z = 3.11$, $p < .001$*	$t = 2.89$, $p = .002$*	$F = 5.03$, $p = .039$*	$F = 8.30$, $p = .016$*	$t = 5.11$, $p < .001$*
Difficulty	$z = -1.38$, $p = .122$	$t = 1.37$, $p = .122$	$F = 1.87$, $p = .182$	$F = 1.25$, $p = .299$	$t = 0.25$, $p = .803$
Eccentricity	$z = 0.76$, $p = .493$	$t = -1.67$, $p = .257$	$F = 0.03$, $p = .964$	$F = 2.14$, $p = .163$	$t = 0.36$, $p = .719$

Note. * $p < .05$. IES = Inverse Efficiency Score, where higher scores indicate poorer performance.

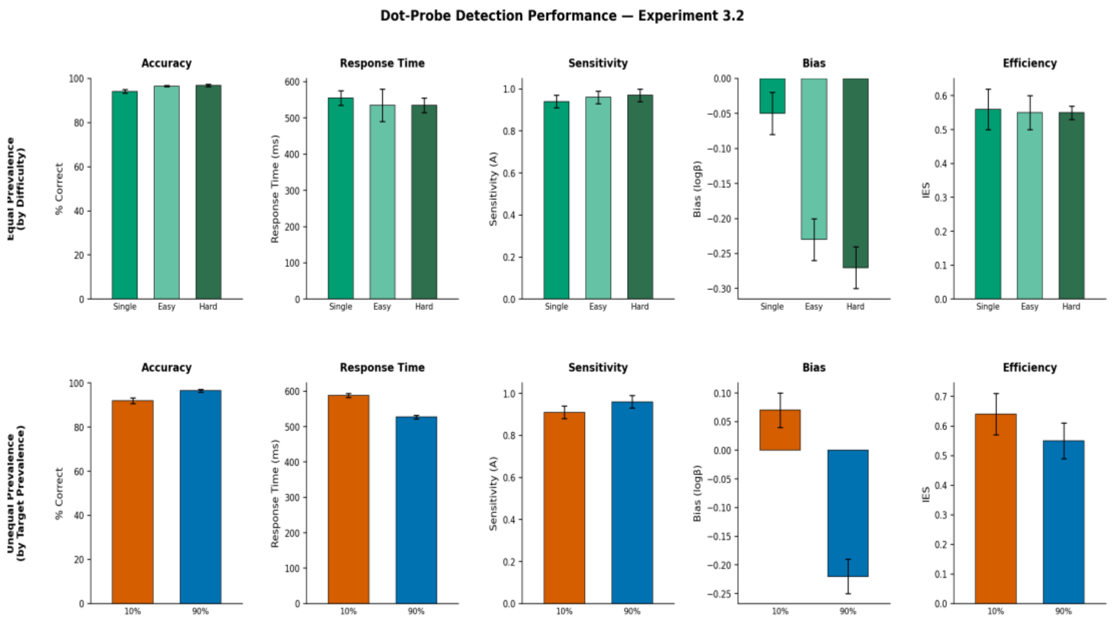


Figure 3.2. *Dot-probe detection performance in equal and unequal target prevalence conditions (Experiment 3.2): accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).*

Note. Bars show group means; error bars show ±SD. Equal-prevalence panels are broken down by letter discrimination difficulty; unequal-prevalence panels are broken down by target prevalence (10% vs. 90%).

Discussion

The results reported in Experiment 3.1 were fully replicated when ensuring pre-emptive eye movements were not made to possible dot-probe locations while letters were being presented in the letter discrimination task. In fact, statistical comparisons across Experiments 3.1 and 3.2 for all measures revealed no significant effects of Experiment (all *p* values for interactions with Experiment > .286; full details of the statistical analysis can be found in Appendix B).

Experiment 3.3

Having established that the effects of low prevalence on subsequent task performance persist with trial-by-trial feedback, Experiment 3.3 explores whether the effects of low prevalence scale proportionally with the extent of prevalence imbalance, using the same sequential letter discrimination and dot-probe detection tasks in a blocked design with progressively increasing prevalence inequality (50/50, 70/30, 90/10). This also enables the exploration of prevalence effects over time. Although this design introduces potential order effects, counterbalancing would confound prevalence level with presentation order, preventing examination of how prior prevalence exposure influences subsequent task performance.

Based on the findings from Experiments 3.1 and 3.2, and consistent with the linear scaling of statistical learning effects in the prevalence literature (Godwin et al., 2016), three predictions were made for Experiment 3.3. First, dot-probe detection performance was predicted to scale parametrically with the degree of prevalence imbalance: performance should be worst in the 90/10 block, intermediate in the 70/30 block, and best in the 50/50 block. Second, this scaling was predicted to be approximately linear, reflecting graded rather than categorical sensitivity to prevalence imbalance, consistent with statistical learning accounts. Third, an exploratory question concerned whether participants would show any improvement across blocks over and above the prevalence effect — specifically, whether accumulated experience with increasing imbalance would allow any strategic compensation.

Method

Participants

An a priori power analysis using G*Power software (Erdfelder et al., 1996, Version 3.1.9.4) indicated a required sample size of 53 participants to detect a small to medium effect size of d = 0.40 for the following parameters: power = 0.95, α = 0.05, β - 1 = 0.95. 53 participants completed the experiment (age range = 18–39 years, M = 22.28, SD = 5.49), 38 of whom were female. All participants self-reported having normal or corrected-to-normal visual acuity. None of the participants had taken part in Experiments 3.1 or 3.2.

Apparatus

The experiment was programmed in PsychoPy (Peirce, 2007; Peirce et al., 2019, Version 2022.2.4) and presented on a 55-inch Samsung Ultra High-Definition TV screen (resolution: 3840 x 2160 pixels, refresh rate: 120 Hz). Participants viewed the screen from approximately 75 cm, although this was not constrained. Responses were made using a PlayStation DualShock 4 Games Controller, with response buttons counterbalanced for 50% of participants.

Design and Procedure

Experiment 3.3 had a repeated-measures design with three within-subjects variables: Prevalence: 5 levels (10, 30, 50, 70, 90), Difficulty: 3 levels (Single, Easy, Hard), and Eccentricity: 2 levels (Near, Far).

Participants completed the experiment in an isolated experimental booth. The experimenter sat out of view of participants to monitor compliance with the task. Following a practice session consisting of 20 random trials, participants completed three blocks of 150 trials. Blocks were presented in a fixed order (50/50, then 70/30, then 90/10) rather than counterbalanced to allow examination of how prevalence effects accumulate across sequential exposure to increasingly imbalanced prevalence ratios. Trial order was pseudo-randomised within blocks for each participant. Participants were permitted to take short self-timed breaks between blocks.

Exclusion Criteria and Analytic Strategy

Exclusion criteria were the same as in Experiments 3.1 and 3.2. This resulted in data being excluded from seven participants. Letter discrimination accuracy was analysed using binomial generalised linear mixed modelling (GLME). Factors examined in the GLME were Item (5: 10, 30, 50, 70, 90) x Difficulty (3: Single, Easy, Hard). Dot-probe detection accuracy was analysed using binomial generalised linear mixed modelling (GLME). Factors examined in the GLME were Item (5: 10, 30, 50, 70, 90) x Difficulty (3: Single, Easy, Hard) x Eccentricity (2: Near, Far). Response times for dot-probe detection were analysed in the same way as the accuracy data using LME. Non-parametric signal detection measures of sensitivity and bias were calculated for each participant from false alarm and hit rate data and analysed using separate ANOVAs using the same factors and levels. Given the systematic progression of prevalence ratios across conditions (10%, 30%, 50%, 70%, 90%), trend analyses were conducted to test whether dependent measures showed relationships with the degree of target prevalence. For mixed effects models (response time and accuracy), Item was coded using orthogonal polynomial contrasts with the linear contrast weighted as -2, -1, 0, 1, 2 for the 10%, 30%, 50%, 70%, and 90% conditions respectively. For repeated-measures ANOVAs (sensitivity and bias), linear contrasts were conducted using the same weighting scheme. Linear trends were tested as single degree-of-freedom contrasts to assess relationships between prevalence and performance. Mixed-model trends are evaluated using t-tests on the linear contrast coefficients.

Results

Experiment 3.3 varied prevalence across a graded set of ratios (50/50, 70/30, 90/10) to determine whether the prevalence cost operates as an all-or-none effect or scales with the degree of imbalance. The results favour the latter: response time, sensitivity, and bias each showed a significant linear trend, growing progressively worse as prevalence declined from 50% to 10%, and efficiency (IES) followed the same graded pattern descriptively, although a formal linear contrast was not reported for this measure (Table 3.6). A comparison of the 90/10 block against the matched condition in Experiment 2.1b, where participants faced 90/10 without prior exposure to other ratios, showed no interaction (all p values > .386; Appendix C), suggesting that this scaling reflects a genuine effect of imbalance rather than carry-over or fatigue from encountering fairer ratios earlier in the session.

Experiment 3.3 tracked performance across a graded run of prevalence ratios (50/50, 70/30, 90/10) to test whether the prevalence cost is all-or-none or scales with how imbalanced prevalence becomes. The significant linear trends observed across response time, sensitivity, and bias demonstrate that more extreme prevalence imbalance produces proportionally stronger influences on subsequent processing. Dot-probe detection accuracy was higher following single letters than letter arrays and decreased as prevalence rates decreased from 90% to 10%. Response times were faster following single letters compared to letter arrays and increased as prevalence decreased from 90% to 10%. Sensitivity was higher following single letters than letter arrays and lower in the 10% prevalence condition compared to higher prevalence conditions. Bias was more liberal following single letters and in higher prevalence conditions. A comparison of the 90/10 block against the equivalent condition in Experiment 2.1b, where participants encountered 90/10 with no prior exposure to other ratios, showed no interaction (all p values > .386; Appendix C), indicating this scaling is not simply a carry-over or fatigue effect from having already experienced fairer ratios earlier in the session.

In sum, Experiment 3.3 shows the prevalence cost is graded rather than fixed: the rarer the preceding target, the larger the cost on the subsequent dot-probe response, and this scaling holds up even after accounting for the order in which prevalence levels were experienced. Details of letter discrimination and dot-probe statistical effects are shown in Tables 3.5 and 3.6. Figure 3.3 shows dot-probe detection performance across five measures: accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).

Table 3.5. *Letter discrimination accuracy, Experiment 3.3*

Effect	*b*	*SE*	*z*	*p*	Pattern
Prevalence	−0.14	0.01	−1.30	.013	Higher errors for equal prevalence and for low-prevalence targets in 70/30 and 90/10 conditions
Difficulty	−0.37	0.27	−0.14	.894	n.s.

Table 3.6. *Dot-probe detection: main effects and linear trends across prevalence levels, Experiment 3.3*

Measure	Prevalence	Difficulty	Eccentricity	Linear trend
Accuracy	z = 1.58, p < .001*	z = 0.15, p = .014*	z = −0.07, p = .951	z = 1.40, p = .162
Response time	t = −3.54, p < .001*	t = 1.79, p = .082	t = 0.14, p = .894	t = −4.12, p < .001*
Sensitivity (A)	F = 4.00, p = .011*	F = 1.00, p = .370	F = 1.00, p = .326	F = 12.84, p < .001*
Bias (logβ)	F = 11.56, p < .001*	F = 3.00, p = .044*	F = 4.41, p = .042*	F = 17.23, p < .001*
IES	t = 6.52, p < .001*	t = 1.65, p = .101	t = 0.67, p = .504	Not formally tested

Note. * p < .05. Linear trend tests whether the measure changes systematically across prevalence levels (10%, 30%, 50%, 70%, 90%). Direction of effects: accuracy and response time were poorer for lower-prevalence targets and for letter arrays vs. single letters; sensitivity was lower and bias more conservative as prevalence decreased. IES = Inverse Efficiency Score (higher = poorer performance); increased monotonically as prevalence decreased (see Figure 3.3).

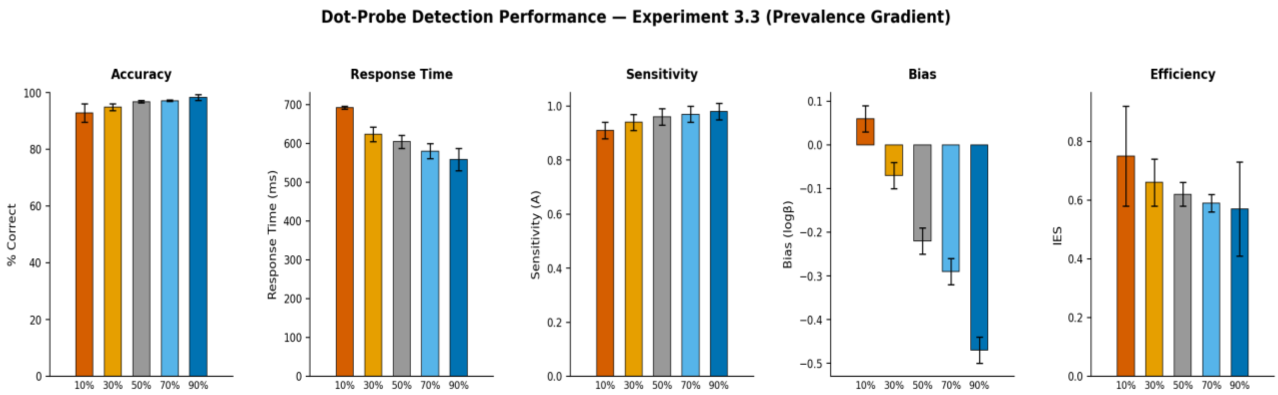


Figure 3.3. *Dot-probe detection performance across the prevalence gradient (Experiment 3.3): accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).*

Note. Bars show group means by target prevalence level; error bars show ±SD.

Discussion

Experiment 3.3 examined whether the effects of prevalence on a subsequent task scale proportionally with the magnitude of prevalence imbalance in the letter discrimination task. The results indicate that the influence of letter prevalence on dot-probe detection scaled linearly, with dot-probe detection becoming slower and less accurate with increasing target prevalence imbalance in the letter discrimination task.

I noted in the Introduction to Experiment 3.3 that the design of the experiment left open the risk of carryover effects whereby participants came to engage with low prevalence targets having already experienced them at higher prevalence rates. The current analysis, although showing that the impact of letter prevalence on dot-probe detection correlates, cannot rule out that carryover effects, such as general practice effects improving overall performance across blocks, habituation to rare targets reducing their salience over time, or strategic adjustments based on accumulated experience with different prevalence rates, affected the results of Experiment 3.3. To provide some insight into the question of carryover effects, the results from the 90/10 condition of Experiment 3.3 were compared with those from Experiment 2.1b. Half of the participants in Experiment 2.1b completed the same 90/10 condition but without prior exposure to other prevalence conditions. Statistical comparison of the data from these two experiments revealed there to be no interaction across experiments (all p values for interactions with Experiment > .386; full details of the statistical analysis can be found in Appendix C).

General Discussion

Experiments 3.1, 3.2, and 3.3 demonstrate the robustness and persistence of the effects of low prevalence in a letter discrimination task on performance in a subsequent dot-probe task, showing that the effects persist despite receiving trial-by-trial feedback on performance in the letter discrimination task, and that these effects scale linearly with increasing prevalence imbalance.

Experiment 3.1 investigated the effect of trial-by-trial feedback and revealed that explicit performance information provides only a modest improvement in low prevalence effects. Although feedback produced some improvement in absolute performance levels, reducing the magnitude of the effects of low prevalence on dot-probe detection, the effects were not eliminated. There remains a question about whether the type of feedback provided to participants was sufficiently effective or whether another type might have eliminated the effect of prevalence completely. For the time being, it is sufficient to note that letter prevalence in the letter discrimination task affects dot-probe detection and that this is not removed by the feedback given in Experiment 3.1.

Experiment 3.2 provided methodological validation for interpreting the effects of low prevalence observed in Experiment 3.1, confirming that differences in dot-probe detection reflect covert attentional allocation rather than systematic differences in overt orienting behaviour.

Experiment 3.3 examined whether the effects of low prevalence on subsequent dot-probe detection scale with the magnitude of prevalence imbalance. The results showed that higher levels of prevalence imbalance in the letter discrimination task are associated with lower performance on the dot-probe task, and this association scales linearly with the degree of prevalence imbalance. Although there remains a methodological question of using a fixed block order of increasing prevalence imbalance, the comparison between the results of Experiment 2.1b and 3.3 suggests the risk of carryover effects impacting the results of Experiment 3.3 is minimal. This finding also suggests that counterbalancing prevalence blocks would not have significantly altered the results, and it would seem wise for future studies to explore this.

In summary, the behavioural experiments reported in Chapters 2 and 3 have shown that manipulating prevalence in a primary letter discrimination task affects performance in a subsequent dot-probe detection task. These effects persist despite being provided with trial-by-trial performance feedback on the letter discrimination task, and scale linearly with the degree of prevalence imbalance. The final experiment presented in this thesis explores the neural underpinnings of the effects of low prevalence on performance in a subsequent task.

Chapter 4. An ERP Study of the Neural Correlates of the Effects of Low Prevalence on a Subsequent Task

Introduction

The behavioural investigations reported in Chapters 2 and 3 showed that prevalence influences subsequent visual judgements. Dot-probes were shown to be detected more slowly and less accurately following low prevalence compared to equal or high prevalence targets in a letter discrimination task. These effects were found to persist: (a) despite receiving feedback on performance in the letter discrimination task implemented to maintain engagement with the task (Experiment 3.1), (b) when controlling for pre-emptive eye movements away from fixation prior to the appearance of the dot-probe which may have influenced the effects (Experiment 3.2), and (c) the effects of prevalence on subsequent task performance scale linearly with increasing prevalence imbalance.

Considering the robust nature of the observed effects of low prevalence on subsequent task performance and their resistance to the measures implemented, Experiment 4.1 seeks to explore the neural mechanisms responsible for these effects to give a broader overview of how and why these effects arise.

Experiment 4.1 uses the same sequential task paradigm as in experiments 2.1, 3.1, 3.2 and 3.3 consisting of a letter discrimination task followed by a dot-probe detection task, with the addition of event-related potential (ERP) methodology. Using ERP methodology enables the exploration of the neural basis of sequential prevalence effects, with a particular focus on the P3 component, as a key marker of attentional resource allocation in visual tasks. The P3 component comprises two distinct subcomponents with different neural generators and functional significance. The P3a is a positive-going waveform typically observed at frontocentral electrode sites (FCz, Cz) with peak latency occurring between 250–280 ms post-stimulus (Squires et al., 1975). This subcomponent is primarily associated with attentional orienting and involuntary attention capture in response to novel or unexpected stimuli, reflecting activity in frontal attention networks (Polich, 2007). The P3b is a later positive deflection with maximal amplitude at centroparietal electrode sites (particularly Pz), peaking between 300–600 ms post-stimulus (Donchin & Coles, 1988; Polich, 2007). The P3b is associated with controlled cognitive processing, working memory updating, and conscious stimulus evaluation (Donchin & Coles, 1988). Both subcomponents' amplitudes are modulated by factors affecting attentional allocation and cognitive resource demands, while latency variations typically reflect differences in stimulus evaluation time (Kutas et al., 1977; Polich, 2007).

Experiment 4.1 examines the P3a and P3b subcomponents, which reflect distinct aspects of cognitive processing that may contribute to effects of low prevalence on a subsequent task. The P3a, associated with attentional orienting and novelty detection (Friedman et al., 2001; Polich, 2007), provides insights into how low prevalence targets capture attention. P3a amplitude is modulated by stimulus novelty, salience, and the degree of attentional orienting required (Squires et al., 1975), with larger amplitudes reflecting greater attentional capture. The P3b, related to controlled processing and working memory updating (Donchin & Coles, 1988; Kok, 2001), indexes the cognitive effort required to process targets. P3b amplitude is sensitive to task difficulty, stimulus probability, and working memory demands (Duncan-Johnson & Donchin, 1977; Kok, 2001), with larger amplitudes indicating greater allocation of cognitive resources. P3b latency reflects stimulus evaluation time, increasing with greater task complexity (Kutas et al., 1977; Polich, 2007). The examination of these ERPs can elucidate whether the observed effects reflect attentional capture mechanisms or controlled processing demands.

Given that the P3a and P3b reflect, respectively, attentional orienting and resource demands associated with stimulus processing, it is likely that the effects of target prevalence on target letter discrimination and dot-probe detection reported in the experiments in Chapters 2 and 3 will be marked in these two measures. The first prediction is that the amplitude of the P3a will correlate negatively with the efficiency of dot-probe detection, given that the speed and accuracy of dot-probe detection is thought to be impacted by attentional orienting to letter targets. The second prediction is that the amplitude of the P3b will correlate positively with the accuracy of target letter discrimination, given that the threshold for letter discrimination should be reflected in the resources required to reach that threshold.[1] The third prediction is that both P3a and P3b amplitudes will show parametric modulation across the three prevalence conditions (30%, 50%, 70%), in line with the linear scaling of behavioural effects observed in Chapter 3. Specifically, P3a amplitude is expected to show a graded increase from high to low prevalence conditions, reflecting progressively greater attentional capture by increasingly rare targets. Similarly, P3b

[1] Predictions relate to the amplitude rather than the latency of the P3, as amplitude measures can directly quantify limited attentional resource allocation between competing tasks (Isreal et al., 1980), with both the P3a and P3b exhibiting amplitude modulations reflecting attentional resource deployment. The amplitude of the P3 correlates with the quantity of information processed during context updating (Johnson, 1986), with the interference between tasks in a dual-task paradigm manifesting primarily in P3 amplitude variations rather than latency changes (Donchin et al., 1986).

amplitude is predicted to increase parametrically from high to low prevalence, reflecting the increased cognitive resource demands associated with processing rarer targets. These parametric patterns would provide neural evidence for the graded nature of prevalence effects on attentional engagement and controlled processing.

Experiment 4.1

Method

Participants

Sample size was determined by balancing statistical power requirements with signal quality considerations (Boudewyn et al., 2017). The factors that guided this decision were: (a) expected effect sizes for P3 modulation in attention-related paradigms (typically d = 0.6–0.8), (b) signal-to-noise ratio requirements for reliable component measurement, and (c) available trials per condition. Based on these considerations, a minimum of 25 participants were targeted to achieve 80% power for detecting condition differences in the P3 component, consistent with recommendations for robust ERP research. 30 participants were recruited to account for withdrawals or potential data loss due to artifacts.

30 participants completed the experiment (Age range = 18–42 years, M = 23.04, SD = 6.53), 20 of whom were female. All participants self-reported having normal or corrected-to-normal visual acuity. Participants were mainly undergraduate Psychology students recruited via opportunistic sampling using the Liverpool Hope University participant recruitment scheme (SONA). Eligible students were awarded partial course credit, and all

participants received a £15 online shopping voucher as compensation for their time. None of the participants had taken part in the studies detailed in Chapters 2 and 3. Ethical approval was granted by the Liverpool Hope University Ethics Committee prior to the commencement of the study. Participants provided written consent and received debriefing information on completion of the experiment.

Apparatus

The experiment was programmed in PsychoPy (Peirce, 2007; Peirce et al., 2019, Version 2024.1.1) using Builder EEG components and additional custom code written in Python. The study was presented on a 47.8 cm Dell E198FP monitor with a resolution of 1280 x 1024 pixels and a refresh rate of 60 Hz. Participants completed the study in a well-lit room seated approximately 57 cm from the monitor.

Continuous EEG data were recorded using a Biosemi2 ActiveTwo amplifier system (BioSemi, Amsterdam, Netherlands) with 64 Ag/AgCl active electrodes. Electrodes were placed according to the extended 10-20 system (Nuwer et al., 1998) with four additional electrodes placed above and below the right eye and on the outer canthi of the left and right eye to record the vertical (VEOG) and horizontal (HEOG) electroculograms. EEG from all channels was acquired at a sampling rate of 512 Hz. The Common Mode Sense (CMS) active electrode and Driven Right Leg (DRL) passive electrode were used as reference and ground electrodes, respectively, as per Biosemi's design specifications. Electrode impedances were maintained below 10 kΩ throughout recording.

Design and Procedure

Experiment 4.1 used a repeated-measures design with three within-participant variables: Item (target prevalence): three levels (30%, 50%, 70%), Difficulty: three levels (Single, Easy, Hard), and Eccentricity: two levels (Near, Far).

Participants completed the same sequential-task consisting of a letter discrimination task closely followed by a dot-probe detection task as previously outlined in Experiments 2.1, 3.1, 3.2 and 3.3. The ISI between letter array offset and dot-probe onset was 105 ms. Participants completed a short practice session consisting of ten random trials before completing four experimental blocks of 100 trials each. The first two blocks were set at a target letter ratio of 50/50, and the last two blocks were set at a target letter ratio of 70/30. The order of trials was pseudo-randomised between experimental blocks and participants. There was a short pause built into the study after every 10 trials and participants were permitted to take short, self-timed breaks between blocks to reduce the effects of cognitive fatigue on performance. As in Experiments 3.1 and 3.2, audio feedback was given on each trial immediately following target letter selection to maintain task engagement, allowing for direct comparison of behavioural effects across studies. This was particularly important in the EEG context, where longer session duration and artifact rejection requirements increase the risk of participant fatigue and disengagement.

Exclusion Criteria

Exclusion criteria for accuracy and response times were the same as in Experiments 2.1, 3.1, 3.2 and 3.3. This resulted in removal of data from 2 participants (6.7% of recruited sample) who achieved less than 90% accuracy on both the letter discrimination and dot-probe detection tasks. A total of 3.4% of behavioural trials were removed for out-of-range response times under 200 ms or over 2500 ms. For EEG, an additional 2 participants were excluded due to excessive recording noise (6.9% of the remaining EEG sample), with 4 further participants having noisy electrodes interpolated at non-critical sites. Following ICA decomposition and epoch rejection, 22.73% of EEG epochs were rejected (30% prevalence: 1,073 trials retained; 50%: 1,788 trials; 70%: 2,503 trials), yielding ERP data from 26 participants.

EEG Data Pre-processing

EEG data preprocessing was performed using the EEGLAB toolbox (version 2024.0; Delorme & Makeig, 2004), ERPLAB toolbox (version 11.03; Lopez-Calderon & Luck 2014) and ERPLAB Studio running on MATLAB (version 2024.a, The MathWorks, Inc., Natick, MA, USA). The continuous EEG data were imported, and channel locations assigned. Next, the data were re-referenced to the average reference. The pre-processed data were then visually inspected, and any bad channels exhibiting persistent artifacts or poor signal quality were identified and marked for interpolation later in the pipeline. The continuous data were then segmented into epochs time-locked to the stimulus events, ranging from -500–970 ms relative to stimulus onset. Independent Component Analysis (ICA) was then applied to the epoched data to identify and remove components related to eye blinks, eye movements, and other physiological artifacts. Any remaining bad channels were interpolated, and a final visual inspection was performed to ensure the data quality was suitable for further analysis. The pre-processed data were low-pass filtered at 30 Hz using a 36 dB finite impulse response (FIR) filter to remove high-frequency noise. The epochs were then baseline corrected using a 200 ms pre-stimulus interval to remove any slow drifts or offsets in the signal. Epoch averages were then computed to derive the ERP waveforms.

In addition to the data previously excluded from analysis, data from an additional two participants were excluded from further analysis due to high levels of noise in the EEG data, potentially caused by movement during the study. EEG data from another 4 participants exhibited high levels of noise, however, this was restricted to one or two electrodes which were which were not in the vicinity of the electrode sites of interest for the analysis (FCz, Cz, and Pz). Noisy electrodes were identified through visual inspection during preprocessing and were excluded from interpolation only if they were located more than two electrode positions away from the sites of interest (FCz, Cz, Pz), ensuring that electrode interpolation did not compromise data quality at the analysed sites, consistent with recommendations for maintaining data quality at sites of interest in ERP studies (Luck, 2014). In total, 26 participants' EEG data were used for ERP analysis. Following ICA, a total of 22.73% of epochs were marked for rejection, and following visual confirmation, were removed from further analysis. The number of trials contributing to the grand averaged waveforms for each condition were as follows: 30% target prevalence: 1,073 trials, 50% prevalence: 1,788 trials, 70% prevalence: 2,503 trials.

ERP Analysis

P3 waveforms were examined in the 30%, 50% and 70% prevalence conditions to explore differences following low, equal and high prevalence targets. Analysis of the P3a and P3b focussed on their respective sites of maximal amplitude, in accordance with previous research (Polich, 2007). Analysis of the P3a focussed on the frontocentral (FCz) and central electrode sites (Cz); analysis of the P3b component focussed on the parietal electrode site

(Pz). The P3a and P3b waveforms were averaged separately for each prevalence condition to produce three sets of ERP waveforms per participant. These were then used to produce grand average waveforms at FCz, Cz and Pz for each prevalence condition. The mean amplitude of the P3a and P3b were measured in the 200–400 ms post-stimulus time window in accordance with previous research (e.g., Luck & Hillyard, 1990). Mean, rather than peak, amplitude was calculated since it is less sensitive to high-frequency noise and provides a more complete representation of voltage changes between time points for all participants, across all conditions and electrode sites (Luck, 2014). Mean amplitude measurement is particularly advantageous when component latency may vary between conditions or participants, as it captures overall amplitude differences without being biased by slight temporal shifts in peak timing (Luck, 2014; Picton et al., 2000).

Analytic Strategy

Data were examined using Linear Mixed-Effect Model (LME) analyses of the relationship between target letter prevalence, discrimination difficulty, and dot-probe eccentricity using the lme4 package in R (Bates et al., 2014). To predict each measure at the trial level, Item (letter identity), Difficulty, and Eccentricity were entered as fixed effects, with intercepts for participant and trial entered as random effects, allowing values to vary between stimuli and participants. Model fitting began with a model containing the full set of two-way interactions which was iterated through different variants until reaching the best-fitting model (any models that failed to converge were excluded). Response times were log-transformed before analysis using standard LMEs. Accuracy (measured as percentage correct and recorded as a binary value) was analysed using binomial generalised linear mixed-effect models (GLMEs). To test whether performance scaled linearly with prevalence, linear contrast analyses were conducted with Item coded using orthogonal polynomial contrasts (1, 0, 1 for 30%, 50%, 70% conditions).

Behavioural Results

For letter discrimination and dot-probe detection accuracy (measured as percentage correct), two factors were examined: Item (3: 30, 50, 70) x Difficulty (3: Single, Easy, Hard). Dot-probe response time data were analysed using linear mixed effect models (LME) with the same factors, but with the addition of Eccentricity (2: Near, Far). Dot-probe response time and accuracy data were combined into an Inverse Efficiency Score (IES) as in Experiments 2.1, 3.1, 3.2, and 3.3. Efficiency data were analysed in the same way as accuracy and response time data.

The behavioural pattern established in Chapters 2 and 3 held up once again under EEG recording: as target prevalence fell, dot-probe detection performance declined in tandem, an effect evident across accuracy, response time, and combined efficiency (IES) alike (Table 4.1, Table 4.2). Letter discrimination likewise showed the familiar low-prevalence cost, with errors decreasing linearly as prevalence increased from 30% to 70%. Figure 4.1. shows dot-probe detection performance by target prevalence level across five measures: accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).

Table 4.1. *Letter discrimination accuracy by target prevalence, Experiment 4.1*

Prevalence	Mean error rate (%)	*SD*
30%	4.78	1.03
50%	3.71	1.50
70%	1.43	0.39

Note. Main effect of Prevalence: $b = -13.72$, $SE = 5.67$, $z = -2.42$, $p = .025$; linear trend: $b = -1.68$, $SE = 0.67$, $z = -2.51$, $p = .012$. Main effect of Difficulty: $b = -7.33$, $SE = 9.15$, $z = -0.80$, $p = .420$ (n.s.). No other effects, contrasts, or interactions reached significance (all z's = 1.21–2.00).

Dot-probe accuracy, response time and efficiency told the same story: performance was worst at 30% prevalence and improved steadily through 50% to 70% (Table 4.2), with significant linear trends confirming this was a graded rather than threshold effect.

Table 4.2. *Dot-probe detection: descriptive means and inferential statistics by target prevalence, Experiment 4.1*

Measure	*M* (30%)	*M* (50%)	*M* (70%)	Main effect of prevalence	Linear trend
Accuracy (% correct)	95.20 (0.50)	95.97 (0.32)	97.00 (0.17)	$z = 4.00$, $p < .001$*	$z = -3.91$, $p < .001$*
Response time (ms)	555 (7.41)	529 (19.63)	466 (22.80)	$t = -3.85$, $p < .001$*	$t = -3.83$, $p < .001$*
IES	5.90 (0.03)	5.55 (0.03)	4.80 (0.03)	$t = -10.93$, $p < .001$*	$t = -11.00$, $p < .001$*

Note. * $p < .05$. Values in parentheses are *SD* (accuracy, response time) or *SE* (IES); accuracy is shown as percentage correct. Difficulty (single vs. easy vs. hard array) was significant for accuracy ($b = 0.67$, $SE = 0.21$, $z = 3.19$, $p < .001$) but not for response time ($b = 7.17$, $SE = 6.78$, $t = 1.06$, $p = .297$) or IES ($b = -0.02$, $SE = 0.06$, $t = -0.38$, $p = .719$). Eccentricity was non-significant for accuracy and response time; IES was lower (better) for far than near probes, $b = -0.16$, $SE = 0.05$, $t = -3.59$, $p = .033$.

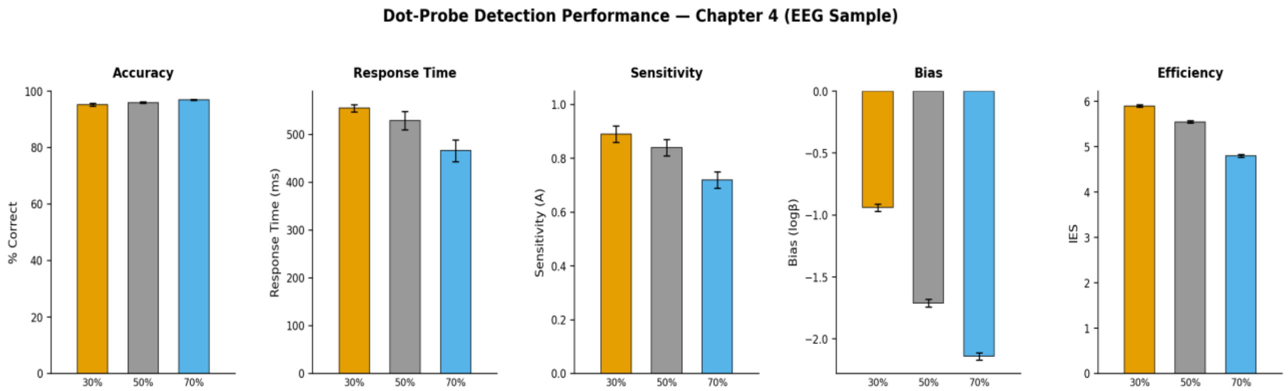


Figure 4.1. *Dot-probe detection performance by target prevalence level (Experiment 4.1): accuracy (percentage correct), response time (ms), sensitivity (A), bias (logβ), and efficiency (IES).*

Note. Bars show group means by target prevalence level; error bars show ±SD (accuracy, response time) or ±SE (IES).

To examine whether participants varied systematically in processing efficiency across prevalence conditions, an additional correlational analysis was performed examining the relationship between efficiency at high versus low prevalence. For each participant, a mean IES for the 30% and 70% prevalence conditions was calculated by aggregating data across all other experimental factors. There was a moderate positive correlation between mean IES in the 30% and 70% prevalence conditions ($r(24) = .41$, 95% CI [.02, .69], $p = .041$), indicating that participants who were more efficient at dot-probe detection in the high prevalence condition tended to be more efficient at dot-probe detection in the low prevalence condition.

The non-parametric signal-detection measures reinforced this picture: sensitivity was lowest at 30% prevalence and bias was least conservative at 30% prevalence, both effects large (Table 4.3).

Table 4.3. *Sensitivity and bias by target prevalence, Experiment 4.1*

Measure	M (30%)	M (50%)	M (70%)	Main effect of prevalence
Sensitivity (A)	0.89	0.84	0.72	$F(2, 26) = 31.05$, $p < .001$*, $\eta^2p = 0.86$
Bias (logβ)	−0.94	−1.71	−2.14	$F(2, 26) = 32.97$, $p < .001$*, $\eta^2p = 0.87$

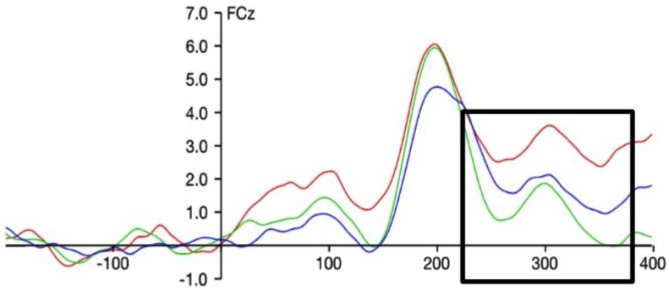
Note. * $p < .05$. Difficulty and Eccentricity were non-significant for both measures (Sensitivity: Difficulty $p = .117$, Eccentricity $p = .228$; Bias: Difficulty $p = .093$, Eccentricity $p = .191$).

In sum, all measures were found to scale linearly with letter prevalence. Dot-probe detection error rates were higher, and response times slower, following 30% prevalence targets than either 50% or 70% prevalence targets, and following single letters rather than letter arrays. Analysis of efficiency data showed that efficiency was poorest following 30% prevalence targets than either 50% or 70% prevalence targets, with better detection of far compared to near dot-probes.

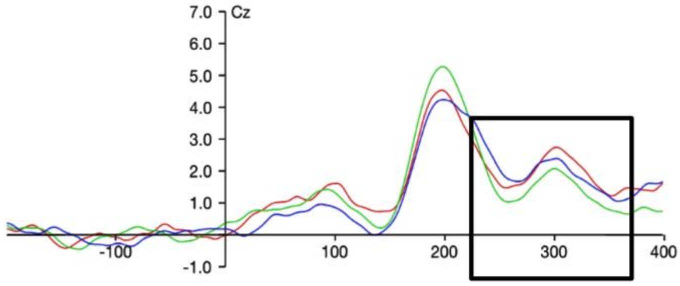
ERP Results

Analysis of ERP data focused on the amplitudes of the P3a (measured at the FCz and Cz electrodes) and the P3b (measured at the Pz electrode). Grand average ERP waveforms were calculated from the average ERP waveforms at FCz, Cz and Pz (see Figure 4.2) for each participant for each prevalence condition. Timing is relative to the onset of the letter array stimulus at 0 ms. Analysis was performed only on trials with correct letter discrimination and dot-probe detection. Scalp distributions of mean ERP amplitudes per prevalence condition and a difference map showing mean amplitude differences between the 30% and 70% prevalence conditions are shown in Figure 4.3.

FCz — Frontocentral Electrode



Cz — Central Electrode



Pz — Parietal Electrode

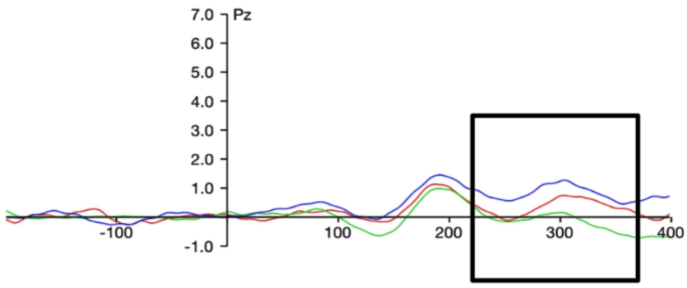


Figure 4.2. *Grand average P3 event-related potential waveforms at frontocentral (FCz, top panel), central (Cz, centre panel), and parietal (Pz, bottom panel) electrode sites by target prevalence condition*

Note. Waveforms are time-locked to letter array onset (0 ms). Positive voltage is plotted upward. Highlighted areas represent time ranges where P3 components typically reach maximal amplitudes. FCz and Cz are frontocentral/central sites where the P3a (automatic attentional capture) is measured; Pz is the parietal site where the P3b (working-memory-related evaluation) is measured.

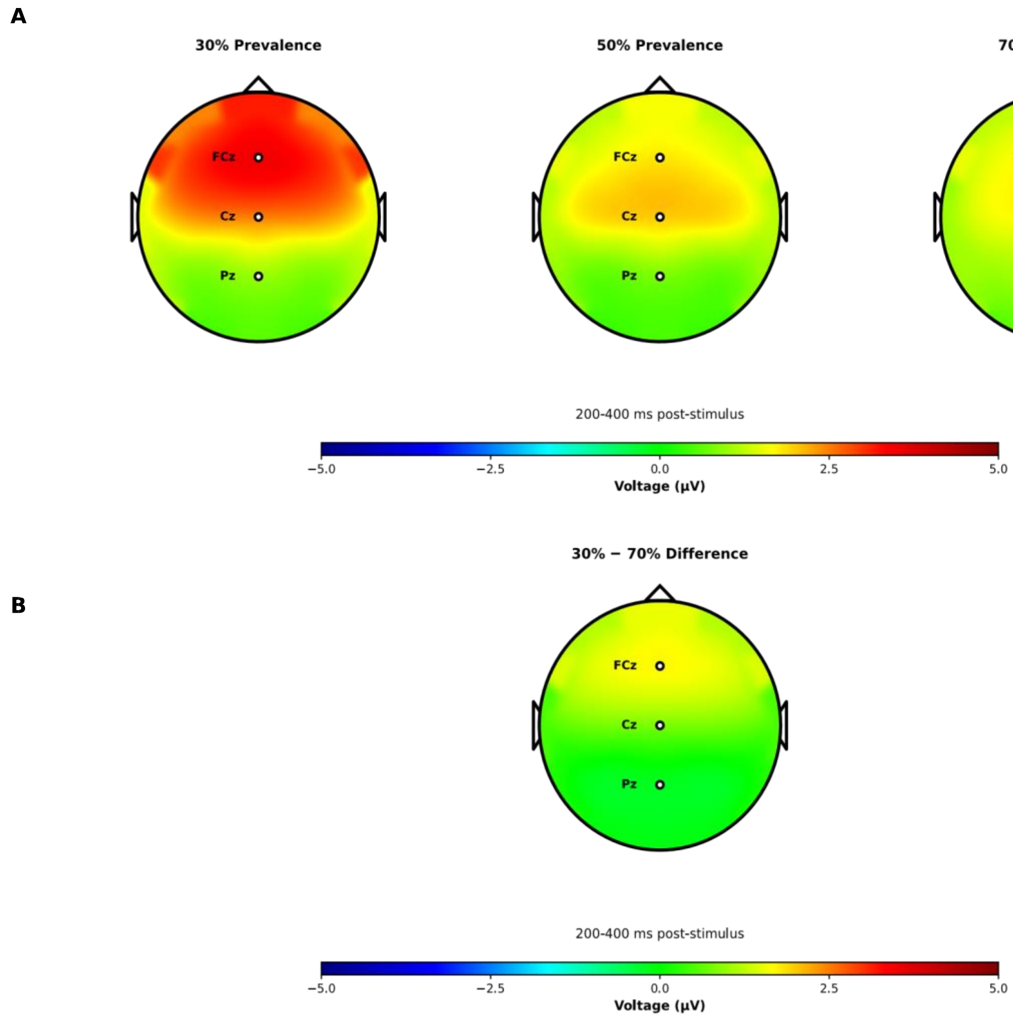


Figure 4.3. (Panel A) *Scalp distributions of mean ERP amplitudes averaged across the 200–400 ms post-stimulus window for 30%, 50%, and 70% target prevalence conditions. The raw-condition maps illustrate a graded shift in P3 distribution from fronto-central to posterior scalp regions as target prevalence increases.* **(Panel B)** *Difference map showing mean amplitude differences between the 30% and 70% prevalence conditions (30% − 70%), highlighting an anterior–posterior dissociation of prevalence effects, with larger positivities over fronto-central electrodes (FCz, Cz) at low prevalence and a posterior maximum at Pz at high prevalence.*

Note. Voltages are displayed in microvolts (μV) using a common color scale across both panels; nose is oriented upward.

The mean amplitude of the P3a (measured at FCz and Cz electrodes) and P3b (measured at the Pz electrode) were examined using a 3 x 3 repeated-measures ANOVA with Greenhouse-Geisser adjustment. Two factors were included in the analysis - Item (3: 30, 50, 70) and Electrode (3: FCz, Cz, Pz; see Table 4.4).

Table 4.4. *P3 amplitude by target prevalence and electrode site (repeated-measures ANOVA)*

Site	M (30%) µV	M (50%) µV	M (70%) µV	η^2p (prevalence effect)
FCz	3.03	1.34	1.65	0.95
Cz	1.92	1.37	1.85	0.92
Pz	0.42	−0.09	0.87	0.89

Note. Main effect of Prevalence: $F(2, 24) = 38.37$, $p < .001$, $\eta^2p = 0.96$. Main effect of Electrode: $F(2, 24) = 39.15$, $p < .001$, $\eta^2p = 0.97$. Item × Electrode interaction: $F(2, 24) = 24.89$, $p < .001$, $\eta^2p = 0.49$. All pairwise prevalence contrasts within each electrode were significant (Bonferroni-corrected *p*'s < .001).

Amplitude and behaviour were linked, but the link depended on prevalence. In sum, the P3a showed strong positive correlations with IES in both the 30% and 70% prevalence conditions, indicating that larger P3a amplitude is associated with reduced dot-probe detection efficiency following both low and high prevalence targets. The P3b showed a strong positive correlation with IES in the 70% prevalence condition only, indicating that larger P3b amplitude is associated with reduced dot-probe detection efficiency following high prevalence targets. Both components showed minimal correlations with IES in the equal prevalence condition (Table 4.5, Figure 4.4).

Table 4.5. *Correlations between P3 amplitude and inverse efficiency scores (IES), by prevalence*

Component	30% prevalence	50% prevalence	70% prevalence
P3a (FCz)	$r(24) = .69$, [.39, .85], $p <$ .001*	$r(24) = -.15$, [−.50, .24], $p =$ .336	$r(24) = .59$, [.27, .80], $p <$ .001*
P3b (Pz)	$r(24) = .43$, [.05, .70], $p =$ .028	$r(24) = -.21$, [−.54, .19], $p =$ .302	$r(24) = .62$, [.31, .81], $p <$ .001*

Note. * survives Bonferroni-corrected significance threshold of $p = .017$. The 30% P3b correlation ($p = .028$) does not survive correction. Positive r indicates larger amplitude associated with poorer efficiency (higher IES).

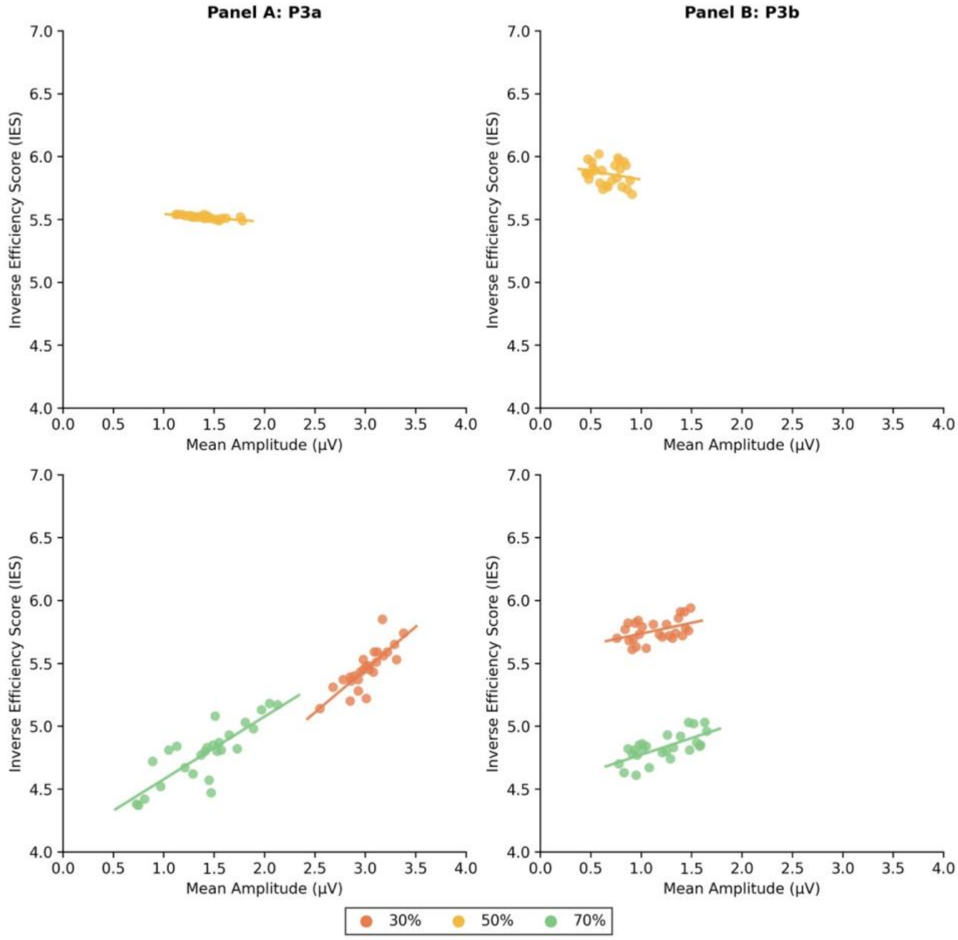


Figure 4.4. *Relationship between P3 component amplitudes and behavioural efficiency by target prevalence level.*

Note. Scatterplots showing correlations between mean P3a amplitude (measured at FCz, Panel A), mean P3b amplitude (measured at Pz, Panel B), and inverse efficiency scores (IES) for individual participants. Each data point represents one participant. Top panel shows data for the equal (50%) prevalence condition, bottom panel shows data for unequal (30% and 70%) prevalence conditions.

Visual inspection of the grand averaged waveforms (Figure 4.2) revealed unexpected differences in earlier ERP components at the FCz electrode, with peaks occurring around 80– 130 ms (labelled P1) and 130–200 ms (labelled N1) post-stimulus. These observations, though not part of the original hypotheses, warranted exploratory examination.

It is important to note that the P1 and N1 components recorded at frontocentral sites differ fundamentally from the classic sensory P1 and N1 components recorded at occipital electrode sites. The occipital P1/N1 reflect automatic sensory processing in the visual cortex (Hillyard & Anllo-Vento, 1998; Luck, 2014, Mangun, 1995). In contrast, positive and negative deflections at similar latencies recorded over frontocentral areas likely reflect different neural generators and cognitive processes, potentially related to attentional control or executive functions rather than early sensory processing (Makeig et al., 2004; Yeung et al., 2004).

Multiple linear regression was conducted to examine whether the amplitudes of the P1 and N1 predicted the amplitude of the P3a component at the FCz electrode site. Data were analysed separately for each prevalence condition. Significance level was set at $\alpha = .05$ for all analyses (see Table 4.6). For completeness, the P1 and N1 were examined at the Pz electrode site to explore whether they predicted P3b amplitude. Consistent with the lack of significant correlations, regression models showed weak and non-significant relationships across prevalence conditions, with all models explaining less than 10% of variance in P3b amplitude and failing to reach significance (all p values > .200). These findings confirmed that early sensory-perceptual processes do not meaningfully predict the controlled resource allocation processes reflected in P3b amplitude.

Table 4.6. *Regression analysis of P3a amplitude on P1 and N1 amplitude, by prevalence*

Prevalence	Model fit	P1 predictor	N1 predictor
30%	R^2 = .52, F(2, 23) = 12.45, p < .001	b = 0.89, t = 3.56, p = .002*	b = −0.42, t = −1.35, p = .198
50%	R^2 = .34, F(2, 23) = 5.93, p = .012	b = 0.68, t = 2.43, p = .021*	b = −0.38, t = −1.31, p = .205
70%	R^2 = .21, F(2, 23) = 3.06, p = .067 (n.s.)	b = 0.45, t = 1.73, p = .095	b = −0.29, t = −1.21, p = .247

In sum, the behavioural data shows reduced efficiency (higher error rates, slower response times) for dot-probe detection following low prevalence targets compared to equal or high prevalence targets. The ERP data reveals the neural basis of these effects. The amplitude of the P3a correlates with response efficiency when target prevalence is low, and with the P3b when target prevalence is high. Early attentional modulation reflected in the P1 partially accounts for the increase in P3a amplitude at low prevalence, with no predictive relationship observed for the P3b. Overall, the ERP data indicates that prevalence effects on later attention and processing reflect additional mechanisms beyond early attentional control functions. Taken together, these effects suggest that factors impacting attentional orienting and resource allocation reduce the processing efficiency of subsequent visual events.

Discussion

Experiment 4.1 investigated the neural correlates underlying the effects of prevalence manipulation in a letter discrimination task on performance in a subsequent dot-probe detection task. The behavioural findings replicate the results reported in Chapters 2 and 3, showing that low prevalence targets impair subsequent dot-probe detection. The ERP data provides insight into the neural basis of these effects, revealing distinct patterns of attentional orienting and resource allocation that explain how target prevalence in one task influences performance in a subsequent task.

The behavioural results confirmed that dot-probe detection efficiency was significantly impaired following low prevalence letter targets compared to equal or high prevalence targets. This pattern was evident in accuracy, response times, and efficiency measures, with participants making more errors and responding more slowly when probes followed rare targets. The correlation between processing efficiency following low vs. high prevalence targets suggests that there are individual differences in susceptibility to prevalence-induced performance costs. Participants who maintained better efficiency following high prevalence targets also showed better efficiency following low prevalence targets, indicating that general processing capacity influences the magnitude of prevalence effects on a subsequent task.

The P3a component showed larger amplitudes following low prevalence targets than equal or high prevalence targets. However, the functional interpretation of P3a modulation requires careful consideration as the P3a literature encompasses multiple proposed mechanisms including automatic attentional orienting to unexpected stimuli, novelty detection, context updating, and inhibition of return (Friedman et al., 2001; Polich, 2007).

In the current paradigm, the P3a enhancement for low prevalence targets most likely reflects automatic attentional orienting triggered by expectation violation. The low prevalence targets, whilst not novel in the strict sense (participants encounter both L and T targets throughout the experiment), violate the statistical expectations established through accumulated experience with target frequencies. The automatic capture of attention by these statistical outliers represents an involuntary orienting response, whereby participants cannot prevent attentional engagement when rare targets appear, regardless of strategic intentions.

However, alternative or complementary interpretations warrant consideration. The P3a may also reflect context model updating (Donchin & Coles, 1988), where rare target appearance necessitates revision of internal probability representations. This updating process would engage prefrontal control mechanisms indexed by the frontocentral P3a distribution. Additionally, novelty detection mechanisms may contribute, as low prevalence targets possess novelty value through their statistical infrequency even when stimulus features are familiar.

The most parsimonious interpretation integrating these perspectives is that P3a reflects a collection of relatively automatic processes triggered by expectation violation: (1) attentional orienting toward the unexpected event, (2) updating of statistical models about target probability, and (3) engagement of prefrontal control mechanisms for processing the rare occurrence. These processes operate largely outside conscious control (evidenced by the persistence of effects despite explicit performance feedback in Experiment 3.1) and involve resource allocation that depletes capacity for subsequent processing.

Critically, the positive correlation between P3a amplitude and behavioural performance costs supports the interpretation that the P3a indexes processes that interfere with subsequent task performance. Whether this reflects pure attentional capture, resource-demanding context updating, or inhibitory processes affecting subsequent processing cannot be definitively determined from ERP data alone. The specific mechanisms underlying P3a generation (orienting, updating, novelty detection) may all contribute and are not mutually exclusive. What matters theoretically is that these processes are (1) automatically triggered by statistical infrequency, (2) resistant to strategic control through feedback, and (3) deplete resources for subsequent visual processing.

Interestingly, the amplitude of the P3a correlated positively with efficiency in both the low and high prevalence conditions (although its magnitude differed across both), but not in the equal prevalence condition. This indicates that larger P3a responses are associated with poorer subsequent task performance and that this association is observed when targets appear with unequal prevalence (either 30% or 70%), but not when targets are equally probable (50%). In reference to the high prevalence condition, this suggests that frequent targets, although expected, may still engage attentional orienting mechanisms, possibly because their high prevalence creates strong expectancies that, when violated by occasional low prevalence targets, trigger reorienting responses. This finding therefore suggests that any imbalance in target prevalence can modulate attentional capture and affect performance in a subsequent task.

The P3b component showed larger amplitudes following high prevalence targets than low prevalence targets. The amplitude of the P3b correlated positively with efficiency only in the high prevalence condition. This suggests that high prevalence targets, by virtue of their frequency, accumulate processing demands across trials that interfere with subsequent task performance. As the P3b is associated with working memory updating and controlled processing (Polich, 2007), larger P3b responses to frequent targets may reflect sustained working memory engagement for maintaining target representations, which then competes with the attentional demands of the subsequent dot-probe task. The dissociation between P3a and P3b effects across prevalence conditions reveals that the effects of prevalence on a subsequent task involve both automatic attentional capture, reflected in changes in the P3a, and controlled processing demands as reflected in changes in the P3b.

The finding that P1 amplitude partially predicts P3a amplitude suggests that the modulation of attention caused by differing prevalence levels may begin at an earlier stage and these changes then cascade through to later orienting responses. Although P1 amplitude across prevalence conditions was not directly tested, the predictive relationship was strongest when targets were rare (30%, $R^2 = .52$) or equally probable (50%, $R^2 = .34$), but absent when targets were frequent (70%, $R^2 = .21$). In the case of low prevalence targets, the predictive relationship between P1 and P3a suggests that the system had detected a novel or unexpected event at an early stage of attention modulation, subsequently triggering stronger orienting responses (reflected in a larger P3a) that interfere with subsequent task performance. The absence of P1 prediction on P3a amplitude in the high prevalence condition indicates that P1 fluctuations no longer drive the magnitude of the subsequent P3a, because the orienting response is reduced or saturated. As a result, frequent targets elicit little need for attentional reorienting, reducing the influence of early attentional modulation on subsequent orienting responses.

Importantly, neither the P1 nor N1 predicted the amplitude of the P3b, suggesting that early attentional modulation does not impact the controlled processing and working memory updating reflected in the P3b. This dissociation provides evidence that P3a and P3b reflect functionally distinct neural processes that contribute to the effects of prevalence imbalance on a subsequent task through different mechanisms.

The present study focused on the P3a and P3b components as indices of attentional capture and controlled processing respectively. However, the EEG data may also contain neural signatures of reduced vigilance, task disengagement, and mind wandering that are relevant to interpreting the effects of low prevalence on subsequent task performance. Mind wandering has been associated with increased alpha power (8-12 Hz) over posterior electrodes, reflecting disengagement from external visual processing (Cooper et al., 2006; Macdonald et al., 2011), and with reduced P3 amplitude to task-relevant stimuli during episodes of task-unrelated thought (Smallwood et al., 2008). Changes in frontal theta activity have also been associated with variations in cognitive effort and mental fatigue during prolonged task performance, although these effects are not specific to disengagement. The contingent negative variation (CNV), a slow cortical potential indexing anticipatory attention, may also provide an additional measure of changes in task preparation and sustained attention (van der Linden et al., 2006). Examining whether alpha power, frontal theta, or CNV amplitude varied across the experiment would provide complementary evidence regarding whether the performance costs observed in low prevalence blocks could be attributed to changes in vigilance, sustained attention, or intermittent disengagement. This represents a potentially valuable direction for further analysis of the existing EEG data and for future research.

Taken together, the behavioural and ERP findings from Experiment 4.1 provide insight into potential mechanisms whereby target prevalence in a primary task may affect performance in a subsequent task. First, the positive correlation between P3a amplitude and processing costs suggests that unequal target prevalence may engage involuntary attentional orienting responses that could temporarily compete with cognitive resources that could be used for a subsequent task. Second, frequent targets additionally engage sustained controlled processing that competes with subsequent task demands. The correlational evidence suggests that both mechanisms may be associated with reduced efficiency of subsequent visual processing, though they operate through distinct mechanisms and are differentially engaged depending on target prevalence. The equal prevalence condition represents a balanced state where neither mechanism dominates, explaining the absence of significant correlations between ERP amplitude and task efficiency in this condition. When targets appear with equal frequency, they elicit neither the attentional capture associated with rare events (reflected in P3a) nor the sustained working memory demands associated with frequent events (reflected in P3b). This balanced processing state may represent optimal conditions where target detection engages standard visual processing mechanisms without imposing additional costs on subsequent tasks.

The final chapter in this thesis consolidates and discusses the findings from the experiments reported in Chapters 2, 3 and 4. This discussion will address their theoretical and practical implications, examine methodological limitations, and propose directions for future research.

Chapter 5. General Discussion

The research presented in this thesis was motivated by a fundamental question: Do the effects of low target prevalence extend beyond the immediate task to influence attention to subsequent visual events? The studies reviewed in Chapter 1 showed that low prevalence targets were detected more slowly, missed more often, and identified less accurately than targets that appeared more frequently and that their possible appearance reduced the span of spatial attention. In sum, the research reviewed in Chapter 1 suggested that item prevalence affects selection and identification decision thresholds and may result in narrowing of the Functional Viewing Field (FVF).

Evidence that prevalence influences immediate target detection is important for understanding performance within a single task. However, real-world visual tasks often require multiple decisions to be made in rapid succession. In the context of these real-world tasks, the key question that emerged from Chapter 1 is whether these prevalence-induced changes in decision criteria and attention remain localised to the immediate task or whether they affect the subsequent allocation of visual attention.

Experimental Findings

The experiments reported in this thesis examined how target prevalence in a primary letter discrimination task affects performance in a subsequent dot-probe detection task. The experiments presented in Chapters 2, 3, and 4 used both behavioural and electrophysiological measures to systematically investigate how prevalence-induced changes in one task affect performance in a temporally proximate but otherwise unrelated task.

In Chapter 2, two experiments explored the question of whether target prevalence in a 2 alternative forced choice (2AFC) letter discrimination task affects performance in a subsequent dot-probe detection task. Experiment 2.1 manipulated relative target prevalence in the letter discrimination task (to manipulate decision thresholds), discrimination difficulty (to vary task demands), and dot-probe eccentricity (to test spatial attention allocation). The results showed that low prevalence targets in the letter discrimination task impaired performance in the subsequent dot-probe detection task. This effect was evident in slower response times, reduced accuracy, lower sensitivity, and more conservative decision criteria. These findings confirm that the prevalence of a prior target has marked effects on the detection of subsequent dot-probes. However, importantly with respect to the idea that prevalence influences the FVF, Experiment 2.1 found no effects of dot-probe eccentricity, nor any interactions between prevalence and eccentricity.

Experiment 2.1 had two limitations. First, exclusion rates due to low accuracy were substantial in the study reporting the UK sample such that 24 participants were excluded from the analysis. While the exclusion of participants in the Chinese sample was markedly less, the comparison across the two studies was affected using different apparatus between experimental sites. Although the broad pattern of results was similar across sites, these methodological inconsistencies necessitated some methodological refinements that were implemented in the studies reported in Chapter 3.

Three new experiments were presented in Chapter 3. These experiments addressed the methodological limitations of Experiment 2.1 but did so in a way that also explored additional theoretical questions. Experiment 3.1 replicated Experiment 2.1 with the addition of trial-by-trial audio feedback on the letter discrimination task. The results showed that feedback produced modest improvements in overall performance levels and reduced the magnitude of prevalence effects on dot-probe detection. However, prevalence effects persisted: low prevalence targets continued to impair subsequent dot-probe detection despite participants receiving explicit performance information. This persistence suggests that feedback may increase general alertness but does not fundamentally alter the underlying mechanisms through which prevalence effects operate. These mechanisms appear resistant to strategic intervention through feedback alone.

Experiment 3.2 used eye tracking to address concerns that participants might make pre-emptive eye movements away from fixation in anticipation of dot-probe appearance. Without eye tracking, such movements could have increased variability in the data and potentially obscured genuine effects. The eye tracking data confirmed that fixation was maintained throughout the letter discrimination task, eliminating this confound and demonstrating that observed prevalence effects reflect genuine differences in covert attention rather than overt eye movements.

Experiment 3.3 examined whether prevalence effects scale linearly with the magnitude of prevalence imbalance by manipulating target prevalence across five levels (10%, 30%, 50%, 70%, 90%). The results revealed a linear relationship between prevalence imbalance and dot-probe detection performance, with dot-probe detection efficiency decreasing proportionally as prevalence imbalance increased. This linear scaling suggests that the visual attention system continuously adjusts attentional allocation and decision criteria based on accumulated statistics of target frequency, rather than implementing categorical shifts in processing strategy. Although the fixed block order of increasing prevalence imbalance introduced the possibility that genuine prevalence effects might be obscured by practice or carryover effects. Practice or carryover effects refer to the fact that participants' performance might improve over the course of the experiment, however, statistical comparison with Experiment 2.1b showed similar performance in the equal prevalence condition, suggesting that there was no significant influence of order effects.

Taken together, the findings from Chapter 3 demonstrated the robustness of the effects of prevalence on performance in a subsequent task. The effects persisted despite feedback, reflected covert attentional processes validated by eye tracking, and scaled linearly with the degree of prevalence imbalance. These results indicate that prevalence manipulation affects subsequent task performance through mechanisms involving both automatic attentional capture and graded statistical learning.

Importantly, none of the studies reported in Experiment 3 found any influence of prevalence on dot-probe location. In this regard, the failure to find an effect of prevalence in dot-probe location in the two experiments reported in Chapter 2 was replicated in the three experiments reported in Chapter 3.

Chapter 4 explored the neural mechanisms underlying the effects of prevalence on a subsequent task using ERPs. Experiment 4.1 recorded EEG while participants performed the letter discrimination and dot-probe sequential task paradigm with three prevalence conditions (30%, 50%, 70%). The behavioural results replicated the findings from Chapters 2 and 3, confirming that low prevalence targets impaired subsequent dot-probe detection.

The ERP data revealed distinct patterns of neural activity reflecting attentional changes. The P3a component, associated with involuntary attentional orienting to novel stimuli, showed larger amplitudes following low prevalence targets compared to equal or high prevalence targets. Interestingly, P3a amplitude correlated positively with processing costs at both low and high prevalence, but not at equal prevalence. This pattern suggests that any imbalance in target prevalence can engage mechanisms that temporarily compete with attentional resources needed for subsequent task performance.

The P3b component, associated with working memory updating, showed a complementary pattern with larger amplitudes following high prevalence targets than low prevalence targets. This suggests that frequent targets impose working memory demands that accumulate across trials and interfere with subsequent task performance.

An unexpected finding was that early attentional components recorded at frontocentral sites also showed prevalence-related modulation. P1 amplitude predicted P3a amplitude in the low prevalence condition and, to a lesser extent, in the equal prevalence condition, but not in the high prevalence condition. This pattern suggests that prevalence-related attentional modulation begins at an early stage of attentional processing and cascades forward to influence subsequent orienting responses. The predictive relationship between P1 and P3a was strongest when targets were rare, indicating that early attentional modulation contributes to the detection of unexpected targets, triggering stronger orienting responses that interfere with subsequent task performance. Importantly, neither P1 nor N1 amplitude predicted P3b amplitude, suggesting that early attentional orienting does not directly influence the later controlled attentional processes and working memory updating reflected in the P3b. The findings from the experiment reported in Chapter 4 provides evidence from neural measures that the effects of prevalence on a subsequent task involve multiple processing stages and distinct mechanisms. The engagement of both automatic (P3a) and updating (P3b) processes, with different patterns across prevalence levels, explains why these effects are robust yet sensitive to prevalence magnitude.

Taken together, the present findings are more consistent with decisional and expectancy-based accounts of low prevalence effects, such as the Multiple Decision Model (MDM), than with perceptual accounts based on Functional Viewing Field (FVF) limitations. Prevalence-related modulations were observed in frontocentral ERP components associated with early attentional modulation and attentional orienting (P1 and P3a), as well as in controlled processing demands indexed by the P3b. The selective coupling between P1 and P3a under low and unequal prevalence suggests that expectancy violations enhance attentional capture, consistent with the MDM's emphasis on decision criteria and orienting biases. As the present analyses did not examine occipital ERP components indexing early visual sensory processing, the data do not directly test predictions derived from FVF accounts. Nevertheless, the expression of prevalence effects at frontocentral stages highlights the contribution of attentional and decisional mechanisms to performance under prevalence imbalance.

The pattern of results reported across Chapters 2, 3, and 4 provides clear evidence about which aspects of identification, decision-making and visual attention are influenced by target prevalence, and which are not. Across all experiments, low prevalence targets in the primary letter discrimination task consistently impaired performance in the subsequent dot-probe detection task. This effect manifested as slower response times and reduced sensitivity in detecting dot probes that appeared after low prevalence targets. The neural evidence from Chapter 4 revealed that this impairment involves two distinct mechanisms: automatic attentional capture indexed by the P3a component, and increased working memory demands indexed by the P3b component. These effects scale linearly with the degree of prevalence imbalance (Chapter 3, Experiment 3.3), indicating that the visual attention system continuously adjusts processing based on accumulated target frequency statistics.

Critically, and as noted above, what prevalence did not affect across all the experiments reported across Chapters 2–4 was the spatial distribution of attention. In every experiment, dot-probe detection performance showed no effect of eccentricity, nor did prevalence interact with the spatial location of the dot-probe. This null finding was consistent and suggests that low prevalence targets in this paradigm did not produce narrowing of the FVF as might have been predicted from the literature reviewed in Chapter 1. However, this conclusion must be qualified by the methodological parameters used in these studies. The dot probes in all experiments were presented at relatively modest eccentricities. It remains possible that prevalence-induced changes to spatial attention would become evident at greater eccentricities or with different spatial distributions of stimuli.

Additionally, prevalence may modulate multiple dimensions of attention simultaneously: while it might affect the size of the FVF it also affects decision criteria and resource allocation. In the current paradigm, the decision-level effects may have been more pronounced than spatial effects, particularly given the brief presentation durations and central fixation requirements. Therefore, while the current findings provide no evidence that prevalence affects the spatial distribution of attention under the tested parameters, they do not definitively rule out the possibility that such effects might emerge under different spatial configurations.

The absence of eccentricity effects across all experiments represents a theoretically important null finding, but one that requires careful interpretation. The current paradigm was not explicitly powered to detect eccentricity x prevalence interactions, and the dot-probe eccentricities used (6.86 and 12.17 degrees) may have been insufficient to reveal FVF narrowing if such effects are small or require more extreme eccentricities to manifest. Future studies could address this by testing probes beyond 15 degrees or using a wider spatial range. However, the null finding may also be theoretically meaningful: it is consistent with the view that prevalence affects general attentional engagement and decision criteria rather than the spatial distribution of attention per se — an interpretation supported by the eye-tracking data from Experiment 3.2 confirming the effects were not due to overt spatial shifts in gaze. To provide stronger statistical evidence for the null, a Bayesian analysis or equivalence testing approach could be applied to the eccentricity data, producing a Bayes Factor or equivalence bounds that quantify the evidence for the absence of an effect.

In summary, the present research demonstrates that target prevalence affects the allocation of attentional resources needed for subsequent task performance such that identification and decision-making are affected. In contrast, there is no evidence that the spatial extent of attention is affected by item prevalence within the tested parameter range. In simple terms, the results reported in Chapters 2–4 are accounted for by attentional capture of low prevalence targets that deplete the resources available to process subsequent visual events. This resource depletion does not change the spatial distribution of visual attention such that the FVF is reduced by the detection of low prevalence targets.

Implications of the Findings

Theoretical Implications

The pattern of results reported across Chapters 2, 3, and 4 provides insight into the mechanisms through which target prevalence in one task might affect performance in a subsequent task. Two theoretical frameworks introduced in Chapter 1 are particularly relevant for interpreting these findings: the Multiple Decision Model (MDM), and the Functional Viewing Field (FVF).

The MDM proposes that prevalence affects both selection and identification stages of target processing. The behavioural findings from Experiments 2.1 and 3.1 are consistent with this framework, showing that low prevalence targets in the letter discrimination task led to more conservative decision criteria in the subsequent dot-probe task. However, the MDM was developed to explain within-task prevalence effects, where selection and identification operate on the same stimulus set. The current findings extend this framework by demonstrating that prevalence-induced changes in decision criteria generalise beyond the immediate task context to influence temporally subsequent but unrelated visual judgements. This suggests that prevalence manipulation affects not only task-specific decision thresholds but also more general cognitive states that persist across subsequent tasks.

The second theoretical framework concerns the allocation of spatial attention. Chapter 1 reviewed evidence that low prevalence conditions may narrow the FVF. If this was the case, performance costs in the dot-probe task should have been greatest for probes presented further from fixation. However, all experiments found no effects of probe eccentricity, nor any interactions between prevalence and eccentricity. Experiment 3.2 also confirmed through eye tracking that prevalence effects reflected covert attentional allocation rather than systematic differences in overt orienting behaviour. These findings indicate that the impairment in subsequent visual processing was not spatially localised. Rather, the results suggest that low prevalence targets influence the subsequent allocation of visual attention through a more general attentional or decision-related mechanism.

The absence of eccentricity effects raises questions about the nature of the mechanism linking performance across tasks. One possibility is that prevalence manipulation affects general attentional engagement that influences subsequent task performance regardless of spatial factors. This interpretation aligns with theories proposing that rare targets trigger post-error-like processing adaptations (Notebaert et al., 2009). However, the current findings differ from typical post-error slowing in two important ways. First, the effects of low prevalence on subsequent task performance were observed for correctly identified low prevalence targets, not errors or misses. Second, the effects scaled linearly with prevalence imbalance rather than showing the categorical shift typically associated with error detection. These differences suggest that while the effects of prevalence on subsequent processing share some similarities with post-error adaptations, they reflect a distinct mechanism related to statistical learning and expectation violation.

Recent theoretical developments have raised important questions about the nature of attentional mechanisms that may inform the interpretation of the current findings. Rosenholtz (2024) argued that visual attention research faces theoretical challenges, with some phenomena traditionally attributed to attention potentially reflecting peripheral vision limitations rather than selective attentional mechanisms per se. Specifically, she proposes that summary statistic encoding in peripheral vision produces crowding effects that could explain certain search performance patterns without invoking attentional selection. This perspective raises the question of whether the prevalence effects observed in the current research reflect genuine attentional modulation or whether they might be better understood through the lens of peripheral vision constraints.

However, several aspects of the current findings argue against a purely peripheral vision account. The effects of prevalence on a subsequent task suggest that prevalence affects processes beyond purely sensory limitations of peripheral vision. If prevalence effects reflected only peripheral encoding constraints, they should not necessarily transfer to a subsequent task with different stimuli and different discrimination requirements. The fact that prevalence-induced changes in the letter discrimination task affected dot-probe detection indicates that prevalence modulates more general cognitive or decision-related processes that persist across tasks. Additionally, the finding that trial-by-trial feedback modestly reduced prevalence effects suggests some degree of strategic control, which would not be expected if effects were determined solely by fixed peripheral vision limitations.

Importantly, the ERP findings reveal that prevalence effects involve processing across multiple stages rather than being localised to any single level. The present findings indicate that early frontocentral components (P1 and N1) and later P3 components reflect related, but functionally distinct, attentional mechanisms. While P1 and N1 index early attentional modulation and readiness, the P3a reflects subsequent attentional orienting to salient or unexpected events, and the P3b reflects controlled processing and working memory updating. The fact that P1 amplitude predicts P3a only in the low prevalence condition is particularly informative, as it suggests that attentional orienting toward rare targets is especially demanding and is driven by early attentional modulation. In contrast, the absence of predictive relationships between early components (P1/N1) and the P3b indicates that controlled attentional processing leading to memory updating is not influenced to the same extent by early attentional modulation under low prevalence conditions. Together, these findings suggest that prevalence imbalance primarily affects automatic attentional orienting mechanisms rather than later controlled processing.

The resource depletion account of the observed effects of prevalence on a secondary task requires careful integration with the electrophysiological findings. The reconciliation lies in recognising that enhanced processing and resource depletion operate at different temporal stages. When a low prevalence target appears in the letter discrimination task, it automatically captures attention due to expectation violation. This attentional capture manifests as enhanced P3a amplitude, reflecting increased allocation of processing resources to the unexpected stimulus. The enhancement occurs during processing of the rare target itself and represents the visual attention system's adaptive response to statistical outliers, devoting additional resources to ensure that rare events are not missed. This pattern is consistent with the oddball paradigm literature showing that rare stimuli elicit larger P3 components than frequent stimuli (Duncan-Johnson & Donchin, 1977; Squires et al., 1976).

The critical insight is that the enhanced processing indexed by P3a enhancement is what causes subsequent resource depletion. Devoting additional attentional resources to processing the rare target means those resources are consumed and temporarily unavailable for the dot-probe task. The resource depletion manifests in behavioural performance costs on the dot-probe (slower RT, reduced accuracy, lower sensitivity) rather than in reduced P3 amplitude to the rare target itself. The resource depletion occurs not because rare targets receive less processing, but because they receive more intensive processing that consumes resources, making them temporarily unavailable for subsequent tasks. This enhanced-then-depleted pattern distinguishes automatic attentional capture (P3a mechanism) from concurrent task resource competition (traditional dual-task interference).

A related methodological consideration concerns eye movement. Rosenholtz (2024) critiques the widespread failure to monitor eye movements in attention experiments, arguing that apparent attentional effects may reflect peripheral vision confounds if observers broke fixation. The current research addresses this concern directly: Experiment 3.2 used eye tracking to confirm that fixation was maintained throughout the letter discrimination task, demonstrating that observed prevalence effects reflect genuine differences in covert attention rather than overt eye movements.

However, it is important to note that Rosenholtz's (2024) critique presents an alternate theoretical perspective on visual attention mechanisms. Moreover, the current experimental paradigm employed stimuli presented primarily in central vision rather than peripheral vision, where Rosenholtz's peripheral encoding constraints would be most pronounced. Several commentaries have challenged aspects of this peripheral vision account (e.g., Godwin et al., 2025; Poth & Poth, 2025), with researchers noting that many attentional phenomena cannot be reduced to peripheral encoding limitations alone. These commentaries underscore that while peripheral vision constraints merit consideration, they do not fully account for the breadth of attentional phenomena observed in controlled experimental settings.

Chapter 1 discussed competing theoretical frameworks for understanding dual-task performance, contrasting capacity-sharing models with economic processing models. The current findings are more consistent with capacity-sharing than economic processing accounts, suggesting that resources consumed by processing low prevalence targets were then not available for allocation to the dot-probe task.

The finding that trial-by-trial feedback modestly reduced but did not eliminate target prevalence effects provides further evidence against purely strategic accounts. If the effects of target prevalence on the subsequent allocation of visual attention were entirely under voluntary control, explicit feedback about performance should have enabled participants to overcome these effects through strategic resource reallocation. The persistence of prevalence effects despite feedback suggests that these effects reflect processes that are resistant to strategic intervention. This interpretation aligns with the electrophysiological evidence showing that low prevalence targets engage involuntary attentional orienting mechanisms.

However, the modest benefit of feedback observed in Experiment 3.1 indicates that strategic factors do play some role in mediating prevalence effects. One possibility is that feedback enables participants to adjust their overall level of engagement with both tasks but cannot overcome the automatic attentional capture triggered by rare targets. This interpretation suggests that prevalence affects subsequent processing through both attentional capture and working memory updating, with feedback selectively influencing the controlled component while leaving automatic processes largely intact.

An important condition for understanding prevalence effects concerns whether they are modality-specific or reflect domain-general mechanisms. The current findings were obtained entirely within the visual modality, with both the letter discrimination task and the dot-probe task requiring visual processing and decision-making. Consequently, it remains unclear whether low prevalence targets in one sensory modality would affect performance in a different modality. This question has important theoretical implications for distinguishing between sensory-level and cognitive-level accounts of prevalence effects.

If the effects of prevalence on a subsequent task are modality-specific, this would suggest that low prevalence visual targets would alter visual attention or decision boundaries, but these changes would not generalise to auditory or tactile judgements. Conversely, if prevalence effects generalise across modalities, this would support domain-general accounts in which prevalence affects decision criteria or cognitive control states that operate across different stimulus types and task contexts, consistent with the MDM emphasis on general decision processes (Wolfe & Van Wert, 2010).

Evidence from cross-modal studies provides insight into this question. Asutay and Västfjäll (2017) demonstrated that auditory-induced arousal can facilitate visual attention in a subsequent search task. In their experiments, participants performed a visual search task with and without task-irrelevant auditory cues that preceded the search. Critically, search times and search slopes decreased with increasing auditory-induced arousal while searching for low-salience targets. This pattern is similar to the prevalence effects observed here, demonstrating that prior context can facilitate subsequent visual target detection, particularly when targets are difficult to discriminate.

The Asutay and Västfjäll (2017) findings suggest that arousal induced by task-irrelevant sounds can facilitate visual attention by decreasing attentional thresholds. Exposure to arousing sounds may bias the attentional competition in favour of high-priority items, consistent with the arousal-biased competition (ABC) account (Mather & Sutherland, 2011). Importantly, this cross-modal facilitation occurred for low-salience targets but not high-salience targets, with the high-salience targets standing out due to their visual saliency, rendering them relatively immune to auditory arousal effects. This modulation by target discriminability parallels the present finding that prevalence carryover effects are stronger when targets are difficult to discriminate, suggesting that both phenomena may reflect similar underlying mechanisms related to decision threshold adjustment and attentional engagement.

The question of modality specificity connects directly to the broader literature on dual-task interference and the attentional blink (AB) discussed in Chapter 1. Classic dual-task experiments examining whether visual and auditory tasks draw on shared or separate attentional resources have produced mixed findings. Some studies suggest modality-specific resources (Treisman & Davies, 1973), whereas others demonstrate cross-modal interference consistent with a central capacity limitation (Jolicœur, 1999).

Prevalence effects may exhibit similar modality specificity. If prevalence manipulations primarily affect early sensory-level processing within a given modality, effects should be strongly modality-specific. However, if prevalence affects later decision-stage processes, as suggested by the P3 modulation observed in the present ERP study, these effects might show partial transfer across modalities, similar to the pattern observed in AB research. The resolution of this question requires direct empirical investigation. Future research could examine whether low prevalence auditory targets impair subsequent visual detection tasks. If such cross-modal interference is observed, this would provide strong evidence for domain-general decision mechanisms and would substantially extend the theoretical scope of prevalence effects beyond modality-specific attentional processing.

The experimental paradigm used in the present thesis shares some temporal characteristics with Rapid Serial Visual Presentation (RSVP) tasks but differs in several critical respects that distinguish the prevalence effects observed here from traditional RSVP phenomena. Like RSVP paradigms, the current task involved briefly presented stimuli requiring rapid target detection. However, unlike RSVP tasks where stimuli appear in a continuous stream, the current paradigm involved discrete, temporally separated tasks: a letter discrimination task followed by a dot-probe detection task, each requiring a distinct response. Traditional RSVP paradigms do not manipulate target prevalence in the manner employed here, where the frequency of specific target letters (T versus L) was systematically varied. Furthermore, RSVP tasks typically assess detection or identification within a single continuous stream, whereas the current paradigm examined how prevalence in one task affects performance in a subsequent, unrelated task. While both paradigms may engage similar attentional mechanisms for processing temporally brief stimuli, the two-task structure and prevalence manipulation of the current paradigm create a fundamentally different processing demand. The key distinction is that prevalence effects in the current research reflect carryover impacts across the boundary between two distinct visual tasks, rather than within-stream processing limitations characteristic of RSVP paradigms.

The AB paradigm is particularly relevant for understanding temporal constraints on prevalence effects. In AB experiments, detection of a first target (T1) in a rapid serial visual presentation stream typically impairs detection of a second target (T2) appearing within 200–500 ms. The temporal structure of the current paradigm was specifically designed to avoid interference from AB effects. In the current experiments, the inter-stimulus interval between the letter discrimination task and the dot-probe detection task (105 ms) was considerably shorter than the AB window. The temporal configuration was intentionally implemented to ensure that any performance decrements observed could be attributed to prevalence-induced attentional or decisional changes rather than to AB mechanisms. Nonetheless, it remains possible that the prevalence effects observed here share some underlying principles with AB phenomena. Both may reflect capacity limitations in attentional resource allocation across successive visual judgements. The critical difference is that AB effects arise from temporal proximity and distractor interference in continuous streams, whereas the prevalence effects in the current paradigm reflect statistical learning and expectation violation that persist across distinct task boundaries.

Moreover, the AB literature demonstrates that attentional resources can be depleted by demanding tasks and recover over time (Chun & Potter, 1995). This temporal recovery function may be relevant for understanding how long prevalence-induced changes to decision criteria persist. If prevalence effects reflect genuine attentional resource depletion, they should show temporal dynamics similar to AB recovery (typically recovering within 500 ms). Alternatively, if they reflect strategic criterion adjustment, they might persist over longer timescales until explicit task demands change.

The temporal persistence of prevalence-induced effects on a subsequent task remains an open question that has important implications for understanding the underlying mechanisms. In the current experiments, the dot-probe task followed closely after the letter discrimination task. The observed carryover effects therefore occurred within a brief temporal window, likely reflecting the maintenance of decision criteria or attentional states in working memory across successive visual judgements. However, it is unclear whether these effects would persist over longer delays or whether they dissipate rapidly once the prevalence context is removed.

Research on attentional control settings suggests that task-specific configurations can persist across trials when switching between tasks is unpredictable, but decay when temporal separation allows for strategic reconfiguration (Leber & Egeth, 2006). Similarly, studies of decision criterion adaptation demonstrate that observers can rapidly adjust response thresholds based on recent experience, but these adjustments may be short-lived without continued reinforcement (Aminoff et al., 2012). In the context of vigilance performance, effects of target prevalence accumulate over minutes to hours, suggesting that prevalence-induced changes to decision criteria can operate over extended timescales when the prevalence manipulation is sustained (Wolfe et al., 2007).

These findings suggest that the carryover effects observed in the current research might reflect relatively transient states that would dissipate with increasing temporal separation between tasks. Future research could examine this directly by manipulating the inter-task interval between letter discrimination and dot-probe tasks. If carryover effects diminish with temporal delay, this would suggest that prevalence-induced changes reflect working memory maintenance of decision criteria rather than longer-term learning or expectancy states. Conversely, if effects persist over substantial delays, this will indicate more durable changes to cognitive control settings or attentional priorities.

The cross-modal arousal findings of Asutay and Västfjäll (2017) also inform this temporal question. Their effects occurred with auditory cues presented immediately before visual search, with sound offset aligned with search array onset. This temporal proximity mirrors the present experimental design where tasks followed in immediate succession. Whether arousal-induced facilitation would persist over longer delays remains unknown, but their finding that effects were strongest for low-salient targets suggests that some form of transient state change occurred that modulated subsequent visual processing.

The theoretical considerations highlight that prevalence effects likely operate through multiple mechanisms operating at different processing stages. Rather than being purely sensory (peripheral vision), purely spatial (FVF), or purely decisional (MDM), the effects appear to reflect a cascade of processes from early attentional modulation through to decision-making and response selection. The P3 modulation and the persistence of effects despite feedback suggest substantial involvement of post-perceptual mechanisms, while the predictive relationship between P1 and P3a at low prevalence suggests that attentional modulation can begin at early stages when targets are rare. This multi-stage account aligns with contemporary perspectives emphasising that "attention" reflects multiple distinct mechanisms rather than a single unitary process.

Practical Implications

The findings reported in this thesis have important implications for applied settings where individuals must detect rare targets while managing multiple concurrent or sequential visual tasks. In medical screening for example, radiologists must examine numerous images where abnormalities appear infrequently, often while switching between different types of diagnostic decisions. The current findings suggest that the effects of low prevalence extend beyond accuracy on the immediate task to impair performance on subsequent visual judgements. This has implications for workflow organisation in radiology departments, suggesting that sequential multiple rare-target tasks may lead to performance costs.

These theoretical considerations also extend to real-world environments where individuals must respond to events of varying prevalence across different sensory modalities and temporal contexts. A particularly relevant example concerns the design of warning systems in vehicles. Modern cars increasingly incorporate auditory alerts for rarely occurring events such as collision warnings, lane departure alerts, and blind spot notifications. If prevalence effects generalise across modalities, as suggested by the cross-modal arousal findings of Asutay and Västfjäll (2017), these low prevalence auditory warnings could either impair or facilitate drivers' subsequent visual detection of road hazards, depending on the arousing properties of the warning sounds. Understanding both the direction of these effects and their temporal duration is essential for designing effective warning systems that enhance rather than compromise safety-critical performance.

Similarly, in security screening, operators must detect multiple categories of threats that vary in frequency while managing other concurrent responsibilities. The linear scaling of prevalence effects with magnitude of imbalance suggests that even moderate differences in target frequency (e.g., 60% versus 40%) can affect subsequent task performance. This finding indicates that training protocols should account for the effects of prevalence imbalance across sequential tasks, rather than treating each screening decision in isolation.

The persistence of prevalence effects despite trial-by-trial performance feedback suggests that simple feedback interventions may be insufficient to eliminate performance costs in sequential task contexts. For instance, training programmes might focus on maintaining consistent attentional engagement across trials regardless of target frequency, rather than relying solely on feedback to improve performance.

Limitations and Future Directions

Several limitations of the current research should be acknowledged. First, all experiments used mainly undergraduate student samples, which may limit generalisability to applied populations such as radiologists, security screeners, or air traffic controllers who perform sequential visual tasks professionally. Professional operators may have developed compensatory strategies or enhanced attentional control that moderates the effects of prevalence on a subsequent task. Future research should examine whether the mechanisms identified in this thesis operate similarly in expert populations or whether expertise confers an element of resilience to prevalence-induced performance costs.

Second, the experiments examined performance under optimal viewing conditions with high-quality stimuli, brief presentation durations, and controlled environments. Real-world detection tasks often involve degraded viewing conditions, variable stimulus quality, interruptions, and fatigue. These factors may interact with prevalence effects to produce larger or qualitatively different impacts on sequential task performance. For example, fatigue might exacerbate prevalence effects if depleted cognitive resources are less able to recover between tasks or might attenuate them if fatigue reduces the magnitude of automatic attentional capture to rare targets.

Third, the experiments used relatively simple stimuli (letters and dots) presented at brief durations under controlled laboratory conditions. Real-world visual search often involves more complex stimuli, longer viewing times, and greater variability in display characteristics. Future research should examine whether sequential prevalence effects generalise to more ecologically valid search tasks, such as luggage screening or medical image interpretation. Such research would establish whether the mechanisms identified in this thesis operate similarly when processing complex, meaningful stimuli that more closely approximate applied contexts.

Fourth, the current experiments examined sequential effects over short time scales, with the dot-probe task following the letter discrimination task by 105 ms. Future research should investigate how long prevalence-induced changes in attentional state persist. Additionally, examining performance across extended trial sequences could reveal whether the effects adapt over time.

Fifth, the experiments used a 2AFC letter discrimination task where both response options corresponded to targets, with prevalence manipulation determining the relative frequency of each target. This design differs from traditional prevalence paradigms where prevalence determines the ratio of target-present to target-absent trials. Future research should examine whether sequential prevalence effects differ between relative prevalence manipulations and absolute prevalence manipulations, as these may engage different cognitive mechanisms. Absolute prevalence manipulations involve different decision processes, as observers must discriminate target-present from target-absent trials rather than discriminating between two target types. The effects of absolute prevalence on subsequent processing may be larger if target-absent trials provide less opportunity for statistical learning or if they engage different decision criteria.

Sixth, the current research did not examine potential interventions that might mitigate the effects of prevalence on a subsequent task. Although Experiment 3.1 showed that trial-by-trial feedback provided only modest benefits, other interventions might prove more effective at mitigating sequential prevalence effects. Variable priority training, where operators practice with different prevalence ratios, might improve adaptability to prevalence shifts. Attentional reset procedures between tasks, such as brief rest periods or engagement in an unrelated task, might allow cognitive resources to recover before the next detection decision. Explicit instructions about prevalence statistics might enable strategic compensation, particularly if individuals understand that low prevalence targets will impair subsequent processing. Future research should systematically evaluate these interventions to identify which are most effective and under what conditions.

Finally, the research did not examine all potentially relevant individual difference variables. Factors such as working memory capacity, attentional control, or personality characteristics might also moderate these effects. A more comprehensive examination of individual differences could identify which populations are most vulnerable to prevalence-induced performance costs and inform targeted interventions.

Additionally, as discussed above, critical questions remain about the modality specificity prevalence effects. Future research should directly test whether prevalence manipulations in one sensory modality affect performance in another modality. Such research would establish whether prevalence effects reflect domain-general decision mechanisms or modality-specific sensory adaptations and would clarify the practical implications for multi-modal warning systems and sequential task environments.

Conclusions

The experiments reported in this thesis demonstrate that target prevalence in a primary task affects performance in a subsequent, temporally proximate, but unrelated task. These effects are robust, persist despite performance feedback, and scale linearly with the magnitude of prevalence imbalance. The absence of eccentricity effects suggests that prevalence affects general attentional or decision-related processes.

The electrophysiological evidence reveals that sequential prevalence effects involve both automatic attentional capture (indexed by P3a modulation for low prevalence targets) and sustained working memory engagement (indexed by P3b modulation for high prevalence targets). These distinct neural mechanisms operate through different pathways, with early attentional modulation (P1) predicting attentional orienting responses for rare but not frequent targets. The dissociation between automatic and controlled mechanisms may explain why prevalence effects are resistant to strategic intervention through feedback while remaining sensitive to the magnitude of prevalence imbalance.

These findings extend current understanding of prevalence effects from single-task contexts to sequential task performance, demonstrating that the influence of target prevalence persists beyond the immediate task to affect subsequent visual processing. This has important implications for applied settings where operators must manage multiple sequential tasks while detecting targets that vary in frequency and highlights the need for interventions that address both automatic and sustained components of prevalence-induced processing costs.

The question of whether prevalence effects generalise across sensory modalities remains an important avenue for future research. Evidence from cross-modal studies suggests that arousal-based mechanisms may facilitate cross-modal transfer of attentional effects, but direct tests of cross-modal prevalence effects are needed. Similarly, establishing the temporal boundaries of carryover effects would clarify whether these effects reflect transient working memory states or more durable changes to cognitive control settings. Addressing these boundary conditions will be essential for developing comprehensive theoretical accounts of how target prevalence influences attention in sequential task contexts.

The present thesis makes several novel contributions to the literature on visual attention and the low prevalence effect. First, it provides, to my knowledge, the first systematic investigation of whether prevalence-induced attentional states transfer across task boundaries to affect a temporally subsequent but structurally independent visual task. Prior research has established that low prevalence targets are missed and detected more slowly within a single task; the current findings extend this to show that these effects have consequences beyond the immediate task context. Second, this thesis provides one of the very few — and possibly the first — direct electrophysiological investigations of the neural correlates of the low prevalence effect in a visual search context, using ERP methodology to identify the P3a and P3b signatures of sequential prevalence effects. Third, the cross-cultural replication of the basic effect across UK and Chinese samples (Experiments 2.1a and 2.1b) provides evidence for the generalisability of the LPE and its sequential consequences across different testing environments. Together, these contributions advance theoretical understanding of how statistical regularities in one task context shape attentional engagement across subsequent visual events, with implications for any applied setting where targets are rare but consequential.

In summary, this thesis has provided a novel contribution to the theoretical understanding of prevalence effects in three important ways. First, it has demonstrated that prevalence effects extend beyond single-task performance to influence subsequent unrelated visual judgements, establishing that these effects reflect persistent changes in cognitive state rather than purely task-specific adjustments. Second, it has provided a mechanistic understanding of how prevalence affects subsequent processing through both automatic attentional capture and sustained working memory engagement, as revealed through dissociable P3a and P3b modulation. Third, it has shown that these effects scale linearly with prevalence magnitude and are resistant to simple interventions, indicating that they reflect fundamental statistical learning mechanisms. Together, the findings of this thesis have been presented in relation to the applied nature of sequential visual tasks, with suggestions for how to practically apply the results in contexts where managing prevalence-induced performance costs is critical.

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Appendices

Appendix A

Confusability Matrix for Distractor Letter Selection

Confusion Matrix

	Response																									
S	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	.633	.006	.002	.002	.004	.008	.006	.020	.016	.040	.052	.013	.005	.027	.006	.007	.004	.065	.011	.005	.001	.004	.008	.024	.007	.024
B	.018	.393	.007	.053	.013	.002	.150	.014	.001	.010	.007	.002	.002	.010	.037	.012	.064	.092	.087	.002	.009	.002	.007	.000	.002	.004
C	.002	.002	.712	.006	.049	.014	.101	.001	.006	.002	.003	.018	.000	.003	.017	.007	.013	.011	.007	.009	.003	.003	.000	.001	.002	.006
D	.004	.035	.006	.680	.004	.003	.010	.003	.002	.043	.002	.002	.002	.008	.042	.060	.023	.018	.014	.003	.016	.002	.004	.001	.006	.007
E	.004	.042	.022	.006	.350	.183	.034	.021	.038	.008	.020	.029	.002	.016	.007	.055	.008	.067	.023	.032	.007	.004	.002	.003	.010	.007
F	.011	.010	.011	.002	.057	.367	.013	.032	.052	.018	.021	.018	.008	.017	.003	.185	.002	.069	.007	.050	.008	.004	.007	.002	.013	.013
G	.007	.029	.050	.018	.018	.002	.599	.009	.002	.004	.001	.004	.001	.009	.051	.009	.103	.034	.023	.007	.013	.003	.002	.000	.000	.002
H	.015	.018	.002	.010	.007	.011	.008	.414	.035	.032	.015	.013	.101	.108	.007	.012	.006	.067	.004	.023	.018	.006	.052	.002	.013	.003
I	.002	.003	.011	.002	.015	.025	.002	.008	.608	.082	.004	.068	.002	.003	.002	.007	.001	.004	.007	.093	.006	.004	.001	.004	.016	.020
J	.008	.004	.003	.005	.002	.007	.004	.026	.078	.647	.012	.024	.005	.013	.004	.007	.002	.007	.006	.021	.046	.013	.015	.006	.018	.018
K	.002	.002	.009	.002	.008	.023	.002	.010	.014	.015	.385	.011	.011	.014	.000	.015	.001	.047	.005	.023	.006	.022	.022	.173	.114	.063
L	.008	.005	.013	.004	.019	.004	.001	.022	.147	.052	.014	.537	.005	.011	.005	.008	.005	.008	.009	.045	.022	.010	.014	.004	.011	.016
M	.005	.011	.005	.003	.006	.009	.004	.151	.006	.012	.055	.003	.437	.072	.006	.018	.005	.052	.006	.024	.014	.007	.039	.027	.021	.002
N	.019	.012	.001	.006	.001	.002	.004	.022	.005	.008	.108	.013	.027	.494	.001	.004	.003	.108	.013	.006	.005	.020	.026	.060	.028	.003
O	.001	.016	.098	.092	.002	.004	.153	.001	.004	.009	.001	.003	.000	.004	.383	.020	.142	.013	.023	.003	.014	.002	.002	.001	.004	.003
P	.018	.023	.017	.032	.018	.084	.015	.022	.002	.008	.005	.005	.006	.003	.015	.567	.007	.088	.021	.006	.013	.004	.005	.003	.006	.007
Q	.005	.014	.106	.083	.001	.003	.183	.003	.001	.011	.002	.007	.001	.002	.252	.004	.249	.011	.028	.000	.016	.003	.004	.001	.003	.006
R	.022	.022	.015	.019	.015	.036	.046	.040	.000	.006	.013	.002	.005	.023	.023	.131	.042	.444	.044	.011	.008	.002	.007	.007	.013	.003
S	.007	.068	.043	.010	.074	.020	.204	.006	.013	.010	.015	.008	.002	.013	.016	.017	.027	.101	.301	.018	.006	.004	.002	.003	.004	.009
T	.004	.002	.003	.002	.004	.069	.002	.013	.168	.036	.007	.031	.004	.012	.002	.025	.001	.011	.002	.520	.007	.013	.002	.006	.032	.022
U	.004	.003	.012	.013	.002	.002	.037	.011	.004	.028	.005	.021	.012	.025	.021	.007	.014	.005	.002	.006	.628	.049	.082	.002	.006	.000
V	.001	.002	.002	.005	.000	.013	.004	.004	.025	.021	.018	.007	.002	.025	.006	.013	.002	.015	.003	.013	.047	.528	.043	.017	.182	.001
W	.041	.014	.001	.005	.003	.007	.006	.068	.004	.013	.157	.009	.089	.083	.007	.020	.007	.127	.008	.002	.013	.005	.187	.100	.013	.010
X	.002	.001	.000	.001	.002	.005	.002	.002	.009	.016	.086	.007	.005	.023	.001	.003	.000	.022	.004	.013	.002	.037	.011	.503	.211	.034
Y	.002	.001	.000	.002	.000	.023	.000	.005	.020	.023	.012	.004	.003	.016	.001	.022	.001	.007	.002	.031	.004	.027	.007	.059	.657	.074
Z	.009	.001	.002	.002	.007	.006	.002	.003	.011	.028	.015	.013	.001	.004	.002	.003	.001	.007	.010	.014	.002	.006	.003	.027	.058	.760

Note—S = stimulus.

Figure A1. *Confusability matrix used to select distractor letters for the letter discrimination task used in Experiments 2.1, 3.1, 3.2, 3.3 and 4.1, taken from van der Heijden, Malhas, & Van Den Roovaart (1984)*

Note. Each entry in the matrix gives the proportion of times that a stimulus letter (row headings) was identified as a response letter (column headings).

Appendix B

Statistical Comparisons Across Experiments 3.1 and 3.2

Letter Discrimination (Equal Prevalence)

A mixed ANOVA with Experiment (3.1 Feedback, 3.2) as a between-subjects factor and Item (L_{50}, T_{50}) and Difficulty (Single, Easy, Hard) as within-subjects factors was conducted on letter discrimination accuracy. The main effect of Experiment failed to reach significance ($F(1, 55) = 1.47$, $p = .231$, $\eta^2_p = 0.03$), indicating that letter discrimination accuracy did not differ significantly between the feedback condition of Experiment 3.1 (M = 2.83%, SD = 1.62) and Experiment 3.2 (M = 2.14%, SD = 1.39). As in the individual experiments, the main effect of Difficulty ($F(2, 54) = 4.89$, $p = .011$, $\eta^2_p = 0.08$) remained significant, with higher error rates for letter arrays than single letters. The main effect of Item failed to reach significance. The interaction between Experiment and Difficulty ($F(2, 54) = 0.78$, $p = .464$, $\eta^2_p = 0.01$) did not reach significance, indicating that the difficulty effect on letter discrimination was consistent across experiments. No other main effects or interactions reached significance.

Dot-Probe Detection (Equal Prevalence)

Accuracy. A mixed ANOVA with Experiment (3.1 Feedback, 3.2) as a between-subjects factor and Item (L_{50}, T_{50}), Difficulty (Single, Easy, Hard), and Eccentricity (Near, Far) as within-subjects factors was conducted on dot-probe detection accuracy. The main effect of Experiment failed to reach significance ($F(1, 55) = 0.28$, $p = .599$, $\eta^2_p = 0.01$), with comparable error rates in the feedback condition of Experiment 3.1 (M = 4.24%, SD = 1.45) and Experiment 3.2 (*M* = 4.15%, *SD* = 1.32). As in the individual experiments, the main effect of Difficulty remained significant ($F(2, 54) = 5.87$, $p = .005$, $\eta^2_p = 0.10$), with higher error rates following single letters than letter arrays. The interaction between Experiment and Difficulty interaction did not reach significance ($F(2, 54) = 0.51$, $p = .605$, $\eta^2_p = 0.01$). No other main effects or interactions reached significance.

Response Time. A mixed ANOVA on response times revealed no significant main effect of Experiment ($F(1, 55) = 1.12$, $p = .295$, $\eta^2_p = 0.02$), with comparable response times in the feedback condition of Experiment 3.1 (*M* = 545 ms, *SD* = 54.22) and Experiment 3.2 (*M* = 552 ms, *SD* = 48.67). No other main effects or interactions reached significance.

Sensitivity. The main effect of Experiment on sensitivity did not reach significance ($F(1, 55) = 0.18$, $p = .675$, $\eta^2_p = 0.00$), with similar sensitivity in the feedback condition of Experiment 3.1 (A = 0.96) and Experiment 3.2 (A = 0.96). As in the individual experiments, the main effect of Difficulty remained significant ($F(2, 54) = 6.42$, $p = .003$, $\eta^2_p = 0.11$), with lower sensitivity following single letters than letter arrays. The interaction between Experiment and Difficulty was not significant ($F(2, 54) = 0.89$, $p = .417$, $\eta^2_p = 0.02$). No other main effects or interactions reached significance.

Bias. The main effect of Experiment on response bias failed to reach significance ($F(1, 55) = 0.34$, $p = .563$, $\eta^2_p = 0.01$), with comparable bias in the feedback condition of Experiment 3.1 (logβ = -0.18) and Experiment 3.2 (logβ = -0.15). As in the individual experiments, the main effect of Difficulty remained significant ($F(2, 54) = 18.73$, $p < .001$, η^2_p

= 0.31), with more conservative bias following single letters than letter arrays. The interaction between Experiment and Difficulty did not reach significance ($F(2, 54) = 1.28$, $p = .286$, $\eta^2_p = 0.02$). No other main effects or interactions reached significance.

Letter Discrimination (Unequal Prevalence)

A mixed ANOVA with Experiment (3.1 Feedback, 3.2) as a between-subjects factor and Item (L_{90}, T_{10}) and Difficulty (Single, Easy, Hard) as within-subjects factors was conducted on letter discrimination accuracy. The main effect of Experiment failed to reach significance ($F(1, 55) = 2.18$, $p = .146$, $\eta^2_p = 0.04$), indicating that letter discrimination accuracy did not differ significantly between the feedback condition of Experiment 3.1 (M = 2.67%, SD = 1.84) and Experiment 3.2 (M = 2.30%, SD = 1.72). As in the individual experiments, the main effects of Item ($F(1, 55) = 21.47$, $p < .001$, $\eta^2_p = 0.28$) and Difficulty ($F(2, 54) = 8.92$, $p < .001$, $\eta^2 p = 0.12$) remained significant. The interactions between Experiment and Item ($F(1, 55) = 0.41$, $p = .525$, $\eta^2_p = 0.01$) and Experiment and Difficulty ($F(2, 54) = 0.62$, $p = .542$, $\eta^2_p = 0.01$) did not reach significance, indicating that the prevalence effect and difficulty effect on letter discrimination were consistent across experiments. No other main effects or interactions reached significance.

Dot-Probe Detection (Unequal Prevalence)

Accuracy. A mixed ANOVA with Experiment (3.1 Feedback, 3.2) as a between-subjects factor and Item (L_{90}, T_{10}), Difficulty (Single, Easy, Hard), and Eccentricity (Near, Far) as within-subjects factors was conducted on dot-probe detection accuracy. The main effect of Experiment failed to reach significance ($F(1, 55) = 3.42$, $p = .060$, $\eta^2_p = 0.06$), with comparable error rates in the feedback condition of Experiment 3.1 (*M* = 4.88%, *SD* = 2.45) and Experiment 3.2 (*M* = 5.76%, *SD* = 2.02). As in the individual experiments, the main effect of Item remained significant ($F(1, 55) = 18.94$, $p < .001$, $\eta^2_p = 0.26$), with higher error rates following 10% prevalence targets than 90% targets. The interaction between Experiment and Item did not reach significance ($F(1, 55) = 0.82$, $p = .369$, $\eta^2_p = 0.01$), confirming that the effect of prevalence on dot-probe detection accuracy did not differ between experiments. No other main effects or interactions reached significance.

Response Time. A mixed ANOVA on response times revealed no significant main effect of Experiment ($F(1, 55) = 0.67$, $p = .418$, $\eta^2_p = 0.01$), with comparable response times in the feedback condition of Experiment 3.1 (*M* = 552 ms, *SD* = 62.14) and Experiment 3.2 (*M* = 558 ms, *SD* = 55.33). As in the individual experiments, the main effect of Item remained significant ($F(1, 55) = 52.18$, $p < .001$, $\eta^2_p = 0.49$), with faster response times following 90% prevalence targets than 10% targets. The interaction between Experiment and Item failed to reach significance ($F(1, 55) = 0.58$, $p = .450$, $\eta^2_p = 0.01$), indicating that the effect of prevalence on response times was consistent across experiments. No other main effects or interactions reached significance.

Sensitivity. The main effect of Experiment on sensitivity did not reach significance ($F(1, 55) = 1.38$, $p = .245$, $\eta^2_p = 0.02$), with similar sensitivity in the feedback condition of Experiment 3.1 (A = 0.95) and Experiment 3.2 (A = 0.94). As in the individual experiments, the main effect of Item remained significant ($F(1, 55) = 14.36$, $p < .001$, $\eta^2_p = 0.21$), with lower sensitivity following 10% prevalence targets than 90% targets. The interaction between Experiment and Item was not significant ($F(1, 55) = 0.29$, $p = .592$, $\eta^2_p = 0.01$), confirming that the reduction in sensitivity following 10% compared to 90% prevalence targets was equivalent across experiments. No other main effects or interactions reached significance.

Bias. The main effect of Experiment on response bias failed to reach significance ($F(1, 55) = 0.89$, $p = .350$, $\eta^2_p = 0.02$), with comparable bias in the feedback condition of Experiment 3.1 (logβ = -0.12) and Experiment 3.2 (logβ = -0.08). As in the individual experiments, the main effect of Item remained significant ($F(1, 55) = 11.73$, $p = .001$, $\eta^2_p = 0.18$), with more conservative bias following 10% prevalence targets than 90% targets. The interaction between Experiment and Item did not reach significance ($F(1, 55) = 0.24$, $p = .627$, $\eta^2_p = 0.00$), indicating that the more conservative bias following 10% prevalence targets compared to 90% targets did not differ between experiments. No other main effects or interactions reached significance.

Appendix C

Statistical Comparisons Across Experiments 2.1b and 3.3

Letter Discrimination (Unequal Prevalence)

A mixed ANOVA with Experiment (2.1b, 3.3) as a between-subjects factor and Item (L_{90}, T_{10}) and Difficulty (Single, Easy, Hard) as within-subjects factors was conducted on letter discrimination accuracy. Note that the Medium difficulty condition from Experiment 2.1b was excluded from this analysis to match the conditions tested in Experiment 3.3. The main effect of Experiment failed to reach significance ($F(1, 87) = 1.52$, $p = .221$, $\eta^2_p = 0.02$), indicating that letter discrimination accuracy did not differ significantly between Experiment 2.1b ($M = 1.05\%$, $SD = 0.51$) and Experiment 3.3 ($M = 1.22\%$, $SD = 0.44$). As in the individual experiments, the main effects of Item ($F(1, 87) = 26.38$, $p < .001$, $\eta^2_p = 0.23$) and Difficulty ($F(2, 86) = 5.12$, $p = .008$, $\eta^2_p = 0.06$) remained significant, with higher error rates for 10% than 90% prevalence targets and for letter arrays than single letters. The interaction between Experiment and Item did not reach significance ($F(1, 87) = 0.47$, $p = .496$, $\eta^2_p = 0.01$), confirming that the prevalence effect on letter discrimination was equivalent whether participants experienced only the 90/10 condition (Experiment 2.1b) or progressed through increasing prevalence asymmetry (Experiment 3.3). No other main effects or interactions reached significance.

Dot-Probe Detection (Unequal Prevalence)

Accuracy. A mixed ANOVA with Experiment (2.1b, 3.3) as a between-subjects factor and Item (L_{90}, T_{10}), Difficulty (Single, Easy, Hard), and Eccentricity (Near, Far) as within-subjects factors revealed no significant main effect of Experiment (F(1, 87) = 2.17, p = .144, η^2_p = 0.02). Error rates were comparable in Experiment 2.1b (M = 3.71%, SD = 2.88) and Experiment 3.3 (M = 4.46%, SD = 2.16). As in the individual experiments, the main effect of Item remained significant (F(1, 87) = 31.45, p < .001, η^2_p = 0.27), with higher error rates following 10% prevalence targets than 90% targets. The interaction between Experiment and Item failed to reach significance (F(1, 87) = 0.53, p = .469, η^2_p = 0.01), indicating that the effect of prevalence on dot-probe detection accuracy did not differ between experiments. No other main effects or interactions reached significance.

Response Time. A mixed ANOVA on response times showed no significant main effect of Experiment (F(1, 87) = 3.18, p = .068, η^2_p = 0.04), with similar response times in Experiment 2.1b (M = 543 ms, SD = 37.82) and Experiment 3.3 (M = 570 ms, SD = 28.64). As in the individual experiments, the main effect of Item remained significant (F(1, 87) = 78.92, p < .001, η^2_p = 0.48), with faster response times following 90% prevalence targets than 10% targets. The interaction between Experiment and Item did not reach significance (F(1, 87) = 0.76, p = .386, η^2_p = 0.01), confirming that the slowing of response times following 10% prevalence targets compared to 90% targets was consistent regardless of prior prevalence experience. No other main effects or interactions reached significance.

Sensitivity. The main effect of Experiment on sensitivity failed to reach significance (F(1, 87) = 0.12, p = .733, η^2_p = 0.00), with comparable sensitivity in Experiment 2.1b (A =

0.95) and Experiment 3.3 (A = 0.95). As in the individual experiments, the main effect of Item remained significant ($F(1, 87) = 24.18$, $p < .001$, $\eta^2_p = 0.22$), with lower sensitivity following 10% prevalence targets than 90% targets. The interaction between Experiment and Item was not significant ($F(1, 87) = 0.38$, $p = .540$, $\eta^2_p = 0.00$), indicating that the reduction in sensitivity following 10% prevalence targets did not differ between experiments. No other main effects or interactions reached significance.

Bias. The main effect of Experiment on response bias did not reach significance ($F(1, 87) = 2.08$, $p = .153$, $\eta^2_p = 0.02$), with similar bias in Experiment 2.1b (logβ = -0.15) and Experiment 3.3 (logβ = -0.24). As in the individual experiments, the main effect of Item remained significant ($F(1, 87) = 35.67$, $p < .001$, $\eta^2_p = 0.29$), with more conservative bias following 10% prevalence targets than 90% targets. The interaction between Experiment and Item failed to reach significance ($F(1, 87) = 0.41$, $p = .524$, $\eta^2_p = 0.00$), confirming that the more conservative bias following 10% prevalence targets was equivalent across experiments. No other main effects or interactions reached significance.