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Unequal attention prioritisation of multiple moving and static targets.

Unequal Attention Prioritisation of multiple moving and static targets

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Abstract

In many everyday situations observers are required to simultaneously attend multiple targets of different importance (e.g. driving, security screenings). This thesis explores participants' ability to unequally allocate their attention to different targets or regions of the visual field in both dynamic (Chapters 2 and 3) and static settings (Chapter 4). In a series of three Multiple Object Tracking experiments (Chapters 2 and 3) evidence is provided for the plausibility to allocate attention unequally across different moving targets (Chapter 2) or regions of the visual field (Chapter 3) in a goal-directed manner. As priority associated with a target or region increased, more attention was allocated to it as indicated by improved tracking performance (for direction of heading judgments) and prolonged eye gaze. Stronger evidence for unequal attention prioritisation is also found in cases of foveal versus peripheral tracking indicating the functional role of eye movements during this task. Alternatively, in a series of four hybrid search task experiments (Chapter 4), evidence is provided for a graded prioritisation of different static targets during visual search, based on the priority (i.e. prevalence: Experiment 4; or reward: Experiment 5) associated with each one. This was indicated by quicker and more accurate responses as target priority increased. When the two forms of priority were combined, results indicated that unequal reward distribution (where lower prevalence items are more rewarded; Experiment 6), was found to diminish the effect of prevalence, compared to an equal reward distribution (Experiment 7) as indicated by faster response times and fewer misses. Results of the current thesis support a flexible structure of our attentional resource which can be unequally allocated in a goal-directed manner. Findings also provide practical implications for training observers in real-life settings on how to unequally allocate their limited attentional resource in an efficient manner.

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Covid-19 impact statement

As a result of the continuous lockdowns in 2020 and 2021, all of my data collection was disrupted for months, like it was the case for many others students. This has induced significant delays to me PhD schedule as it took me a lot of months to complete data collection for the majority of the laboratory experiments of this thesis. After seeing the difficulty and time-consuming process of running laboratory eye-tracking experiments during the pandemic, I decided to slightly change the focus of my PhD in order to adapt to the new reality we all had to deal with. As a result, I decided to read into a different kind of literature, which however was still related to my broader topic of attention, and design a new set of studies which would be able to run online. Although this was a really stressful and time-consuming process with a lot of uncertainty, with the advice of my supervisors, I came up with another research question and executed four experiments online. This ended up being a really interesting aspect of my PhD which fits well with the series of my laboratory experiments and offers a more holistic answer to my overarching research question regarding unequal attention prioritisation. This experience also allowed me to develop new skills and knowledge on performing online research which will undoubtably be really useful for my future career.

Author’s Declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's *Regulations and Code of Practice for Research Degree Programmes* and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

Signed: [redacted] Date: 02/02/2023

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Chapter 1 General Introduction

1.1 Thesis Overview

In many everyday situations observers are required to attend multiple targets at the same time in contexts where these are either moving (e.g. driving, sports playing etc) or remain static (e.g. medical X-rays; airport security screenings). However, little attention has been given by vision researchers to how our attention might be allocated *unequally* when these targets are of different importance. This thesis explores participants' ability to unequally allocate their attention to different targets or regions of the visual field in both dynamic (Chapters 2 and 3) and static settings (Chapter 4). In a series of three Multiple Object Tracking experiments (Chapter 2 and 3) evidence is provided for the plausibility to allocate attention unequally across different moving targets (Chapter 2) or regions of the visual field (Chapter 3) in a goal-directed manner. As priority associated with a target or region increased, more attention was allocated to it as indicated by both improved tracking performance (for direction of heading judgments) and prolonged eye gaze. Stronger evidence for unequal attention allocation is also found in cases of foveal versus peripheral tracking indicating the functional role of eye movements during this task (Experiment 3). Subsequently, in a series of four hybrid search task experiments (Chapter 4), evidence is provided for a graded prioritisation of different static targets during visual search, based on the priority (i.e. prevalence: Experiment 4; or reward: Experiment 5) associated with each one. This was indicated by quicker and more accurate responses as target priority increased. The two forms of priority were then combined to explore their interaction. An unequal reward distribution (where lower prevalence items are more rewarded; Experiment 6), diminished the effect of prevalence, compared to an equal reward distribution (Experiment 7) as indicated by faster response times and fewer misses. Results of the current thesis offer support for a flexible structure of our attentional resource which can be unequally allocated in a goal-directed manner in both dynamic and static contexts. Current findings also provide important practical implications for training observers in real-life settings on how to unequally allocate their limited attentional resource in an efficient manner.

The focus of the current thesis is visual attention and how this is *unequally* allocated across different targets or regions of the visual field in both dynamic and static contexts. Before exploring the particular aims and experimental manipulations of the current thesis in the empirical Chapters 2, 3 and 4, Chapter 1 aims to give an overview of attention research over the past decades and introduce the relevant concepts based on which findings of the current thesis will be discussed.

1.2 Attention

To be able to properly function in our complex environments we are constantly required to perceive different moving or static targets and integrate visual information from multiple different sources in order to move around, interact with objects, and make decisions. For example, when driving we have to attend to other cars in the road, to pedestrians, to road signs etc in order to make a decision of taking a turn, or changing our speed. Similarly, when searching for our friends in the crowd or for a particular book on the bookshelf we have to allocate our attention to different potential targets (people or books) and decide whether they are what we are looking for and if not, continue searching. In all cases, we are required to allocate our attention to multiple targets or regions of the visual field, process the relevant visual information and ignore the irrelevant details.

Attention is referred to as the process of concentrating mental focus to specific tasks and stimuli, in an objective or subjective manner, while disregarding other perceivable information (Rensink, 2015). Attention has been the focus of research for many cognitive scientists over decades (see for example Itti et al., 2005; Pashler, 1999; Wright, 1998). Attention has been referred to as a limited cognitive resource that enables perception and conscious processing of information (Hatfield, 1998). Alternatively, other characterisations of attention refer to this as a selective process of choosing to filter specific information based on global considerations (Broadbent, 1982). These considerations are influenced by both endogenous (i.e. top-down cognitive influences) and exogenous (i.e. bottom-up perceptual influences) factors (these are explained in more detail in section 1.8 of this thesis).

Different types of attention and various theoretical frameworks have been identified over time. Research into attention initially began with the development of different bottleneck theories that argued that selective attention works like a bottleneck, restricting the flow of information intake allowing us to attend to relevant sensory input while blocking the processing of other irrelevant information. Such theories include Broadbent's (1958) Filter Model which proposes that all sensory information enters a buffer and is processed like a filter where some information is selected to be processed first, based on different factors like attributes of the stimuli, and some other information stays in the buffer for later processing. According to this model, sensory information that is not treated can potentially fade away. Treisman (1964) further developed the Filter Model and proposed the Attenuation Theory which supports that unselected sensory information which is not processed and stays in the buffer is not eliminated, but rather attenuated by the filter such that it is still processed yet at a decreased level.

In the context of visual attention, several analogies and models have been developed. Posner (1980) first introduced the idea of attention functioning like a ‘spotlight’ which is allocated in our visual field based on endogenous (i.e. top-down and goal-driven) or exogenous (i.e. involuntarily driven by stimulus saliency) cues available at the time. Whatever items or stimuli fall within that spotlight are processed while the rest is selectively ignored. Eriksen and St James, (1986) developed the analogy of an attentional ‘spotlight’ into an analogy of an attentional ‘zoom lens’ according to which attentional field and area of focus can vary in size depending on the task demands something which was not initially supported by Posner’s model. In later years, Awh and Pashler (2000) developed a different attentional analogy which acknowledged the possibility of multiple attentional spotlights that divide attention to different non-contiguous locations at the same time. In particular, Awk and Pashler (2000) provided evidence for the ability of participants to allocate attention to targets presented in different hemifields, indicating some flexibility in attentional deployment.

More recent views argue that visual attention is not a single process but rather a collection of several processes, each with a unique function and underlying mechanism (Rensink, 2009, 2013). Rensink (2015) developed a taxonomy which divides attention in several underlying processes and explores the links between them as well as how different sub-processes can be used in different contexts and tasks to allow us to make sense of the visual world. Figure 1, displays this taxonomy which is a suggestion of potential subdivisions of functions associated with visual attention. According to this taxonomy, functions of attention can be subdivided into *orientation* (i.e. access to a specific set of information from the environment) and *integration* (i.e. forming particular associations of the visual input), where the former is concerned with collecting the relevant information from the environment and the latter with forming associations of this information to be able to guide actions. *Orientation* can then be divided further into the sub-processes of *sampling* (i.e. collecting important/relevant information form the environment) and *filtering* (i.e. discarding unnecessary/irrelevant information from the environment). *Integration* can be divided into the sub-processes of *binding*, (i.e. association of visual information), *holding* (i.e. coherent representation of visual information over time) and *individuating* (i.e. processing unique information of a visual item or object). Each of these sub-processes facilitates the execution of different real-life tasks. For example, representations created by attentional binding allow for recognition of different objects, shapes and characters in our visual world. Similarly, the process of holding permits the preservation of these representations over time which can aid execution of different tasks like tracking of moving items. Alternatively, the process of individuating involves acknowledgement of unique information and identities of an item and therefore allows for prioritisation of search or subitizing. Similarly, Hommel et al. (2019) further argue that the concept of 'attention' has too many meanings to be treated as a unitary construct or neural system and they instead propose a synthetic/constructivist approach of investigating attention which highlights the importance of considering different mechanisms involved.

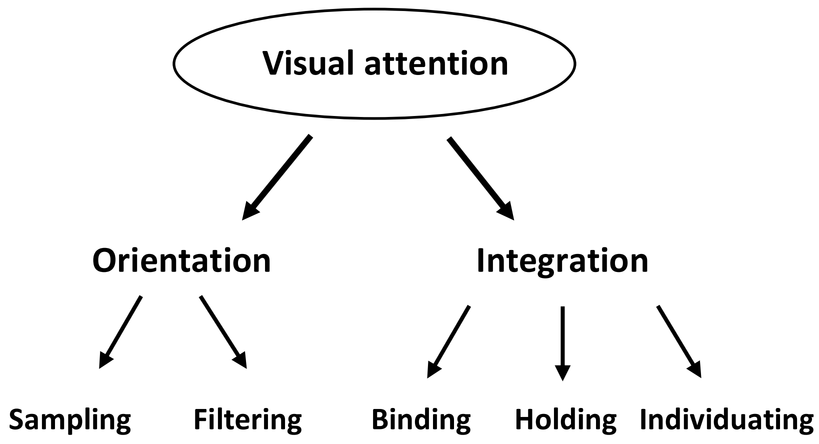


Figure 1. Taxonomy of visual attention, developed by Rensink (2009; 2013; 2015), illustrating potential subdivisions of different processes. Several of these distinctions could be segmented further.

1.3 Divided attention

One important aspect of attention that is relevant to the current thesis, is divided attention which refers to the process of simultaneously allocating focus to different tasks, target features or locations (Shapiro, 2009). An abundance of evidence suggest that attention can be split between different targets (Chong & Treisman, 2005; Emmanouil & Treisman, 2008) and target features (Bichot et al., 2005; Hopf et al., 2000; Maunsell & Treue, 2006; Müller & Ebeling, 2008). In particular, evidence has been provided that multiple features of the same object like colour, shape or orientation can be attended in parallel without any compromise to accuracy or response time performance (Michie et al., 1999; Saenz et al., 2003).

Similarly, evidence exists regarding observers' ability to divide their attention across multiple spatial locations as well (Adamo et al., 2008; McMains & Somers, 2004; Müller et al.,

2003) with some of the initial evidence deriving from different cueing tasks, in which better performance was observed for targets appearing in the cued location versus targets appearing in the uncued location (Eriksen & James, 1986; Luck et al., 1994; Posner & Petersen, 1990; Posner, 1980). This suggests that observers can preferentially divide their attention to different regions of the visual field depending on different cues available.

Additionally, Awh and Pashler (2000) investigated participants' ability to report identity of digits at two different spatial regions on the screen. Participants exhibited similar accuracy levels when two targets were simultaneously presented on the two screen regions, compared to when they were presented on a single screen region, indicative of their ability to divide their attention. Interestingly, participants' accuracy improved when the two targets appeared in different hemifields. Alvarez and Cavanagh (2005) provided further support for these findings showing that there is an independent tracking capacity for the left and right hemifields. In particular, participants were able to successfully track two moving targets which were presented in non-contiguous locations, whether bilaterally (i.e. in different hemifields) or unilaterally (i.e. in the same hemifield) and up to four targets when those were presented unilaterally. Findings therefore provide evidence for divided attention as well as for an independent attentional resource for each hemifield. Adamo et al. (2008) even found that not only can participants divide their attention across two non-contiguous locations, but they can also maintain two different attentional control sets, also known as behavioural goals, across these two distinct spatial regions.

However, it is important to note that methodology and task design should carefully be considered when assessing evidence for divided attention across spatial regions. For instance, Jans et al. (2010) argue that the majority of these investigations fail to employ tasks which allow for a true and representative investigations of attentional division. In particular, according to Forster and Lavie (2008) and Lavie (1995) high perceptual load is a requirement for inducing concentration of attentional resource therefore, a task that is too easy is unsuitable for investigating divided attention. Furthermore, a task with long stimuli presentations can possibly allow for quick movements of attention between target locations and therefore will fail to investigate whether attention can be simultaneously split between these locations at a given instance. Although there is abundance of evidence suggesting the plausibility of dividing spatial attention, before making conclusive inferences for the plausibility of this process, careful consideration is needed regarding the methodology and paradigms used to collect this evidence.

1.4 Capacity and structure of the attentional system

In order to further comprehend the process of attention allocation and the extent to which this can be divided across different targets or regions of the visual field, it is critical to investigate the capacity and structure of our attentional system and how these can change depending on task demands. The process of attention allocation can be challenged by various factors like high number of targets (Barrett & Zobay, 2014; Drew et al., 2011; Liu & Jigo, 2017), low target saliency (Krummenacher et al., 2001; Töllner et al., 2011), closer proximity between items (Franconeri et al., 2008; Tombu & Seiffert, 2008) and smaller target size (Bettencourt & Somers, 2009). Such limitations suggest a finite attentional resource which can be distributed to different items or regions of our visual field (Carrasco, 2011; Lennie, 2003). On average humans are found to be able to allocate their attention to 4 targets at the same time (Alvarez & Franconeri, 2007); interestingly though, it has also been found that participants can simultaneously search for up to 100 items if well-practised, such that the representations of these targets are well-encoded in observers' long-term memory (Drew et al., 2017; Drew & Wolfe, 2014; Wolfe, 2012b). Nevertheless, for items which are not practised, higher multiple target costs (i.e. lowest accuracy and higher response times) are generally observed as the number of the items to be processed increases (Mestry et al., 2017; Stroud et al., 2019). This highlights the need to investigate attention allocation over *multiple* targets in order to find way to increase the efficiency and the accuracy with which observers divide their attention to numerous targets at the same time (Ort & Olivers, 2020).

The structure of our attentional resource is debated, with people arguing for either a fixed or a flexible attentional structure (for a review see Meyerhoff et al., 2017). Fixed theories argue in favour of a set structure of our attentional resource which is devoted in the same way to all objects being attended, irrespective of potentially different properties and identities (Cavanagh & Alvarez, 2005; Pylyshyn 1989; 2001; 2007). To the contrary, flexible accounts support the existence of a constant availability of attentional resource which can be dynamically allocated depending on task demands and targets priorities (Alvarez et al., 2005; Alvarez & Franconeri, 2007). Particular examples of these theoretical frameworks will be given in section 2.2.2 of this thesis. The findings of current thesis will be interpreted in relation to these theories and to the potential need to update these models based on more recent findings on attention allocation derived from both the current thesis and other recent experimental investigations in the relevant literature.

1.5 Unequal attention allocation

It is significant to bear in mind that the majority of the theoretical frameworks regarding the structure and capacity of our attentional resource are primarily based on studies looking at *equal* attention prioritisation in contexts where all targets to be tracked or searched for are of equal importance. However, this is unlike real-life settings where we are often required to allocate our attention unequally to different targets or regions of the visual field. In such cases we need to prioritise the processing of some information versus other which nonetheless requires *some* attention. For instance, a football goalkeeper is required to pay more attention to the player with the ball, but also has to pay attention to other players in close proximity who are of less but not completely negligible importance. Although unequal attention allocation to multiple targets is highly prevalent in real-life settings, it still remains relatively understudied in attention literature.

Nevertheless, some experiments have already investigated settings where participants allocated different proportions of their focus to different aspects of targets. For instance, Miller & Bonnel (1994) used a line-length discrimination task to investigate whether observers can divide their attention unequally between two stimuli which were simultaneously presented on the display, one on the left and one on the right side of the screen. Sensitivity to changes in each line stimulus improved with the amount of attention allocated to that side, indicating that participants allocated their attention unevenly to both stimuli during a single trial.

Similarly, Fitousi (2016) asked participants to allocate different proportions of their attention to two different parts of a face image (i.e. top and bottom) and assess their similarity to a 'study' image which was shown to the participants at the beginning of each trial. The higher the proportion of attention participants were told to allocate to a face part, the better their performance was in detecting its similarity with the 'study' image. The findings therefore, provide support for participants' ability to allocate different amounts of their attention to different parts of a single object, based on top-down instructions.

Atkinson et al. (2018) examined whether manipulating probe frequencies of coloured shapes could influence the amount of attention allocated to them. In particular, researchers explicitely informed participants that accurate recall of a shapes of a specific colour would be rewarded more (i.e. higher probe frequency) than of shapes of other colour. Participants exhibited higher accuracy (indexed as proportion of trials in which the colour was accurately recalled) for coloured shapes with higher probe frequency. These findings therefore indicate more attention allocation and improved visual working memory for targets with higher probe frequency, providing further evidence for unequal attention prioritisation of different colours.

The current thesis consists of an investigation of unequal attention prioritisation of different targets or regions of the visual field in both dynamic and static contexts. Findings are expected to offer a novel insight in the attention literature in relation to how effectively can observers allocate attention to multiple targets or regions of the visual field, based on top-down instructions and in relation to the structure of our attention resource, given that the majority of past investigations were concerned with *equal* attention allocation.

1.6 Tasks used to investigate attention allocation

Many different tasks have been used in the vision literature to investigate division of attention and how attention is allocated to different targets and/or regions of the visual field. In the current thesis, two experimental paradigms will be used in separate experiments:

Multiple Object Tracking (MOT) and Visual Search tasks. Both of these tasks are extensively studied paradigms for studying attention to dynamic and static objects, respectively. In the current thesis results from these two different tasks are interpreted together to offer a more holistic investigation of attention allocation and allow for more conclusive inferences to be made. In particular, given the latest notion in the relevant literature that attention is not a single process but rather a collection of underlying processes, each with its own functions (Rensink, 2009; 2013; 2015), it is important to use a wide range of experimental paradigms to support a single conclusion as different underlying processes of attention might be involved in each task. Modifications of the classic MOT and visual search tasks have been made for the purposes of the experimental manipulations in the current thesis. However, before looking into those in detail it is important to first give an overview and brief description of the typical versions of these tasks and their use in attention literature.

1.6.1 Multiple Object Tracking

The Multiple Object Tracking (MOT) task was initially developed by Pylyshyn and Storm (1988; for review see Meyerhoff et al., 2017). MOT tasks are used to assess how attention is divided and allocated in dynamic scenes with multiple moving objects (Huang et al., 2012; Kunar et al., 2008). In typical MOT tasks participants are presented with a number of identical moving stimuli on the screen, some of which are identified as targets at the beginning of each trial. Participants are initially required to keep tracking the targets amongst visually identical distractors while they all undergo a period of motion. Then at the end of each trial all motion ceases and participants decide on the status of one of the items (i.e. whether it was a target or distractor) or are required to mark all targets in the display.

Alternatively in some other cases, participants are questioned on one of the targets and have to report its trajectory or position (Crowe et al., 2019; Howard et al., 2017).

The MOT task is used frequently in experiments for investigating attention as it captures key aspects of the real-world experience of attention allocation due its dynamic element and the presence of multiple items, targets and distractors (Scholl, 2009). For example, in many real-life situations like driving, sports playing, hunting or even just road crossing, observers are required to attend to multiple moving targets. Additionally, participants' behaviour during a MOT task is thought to be a more valid reflection of real-life settings as they are required to exhibit sustained attention over a period of time and actively engage in the task to keep tracking of moving items, as opposed to traditional spatial cuing studies where participants are solely viewing visual stimuli in a more passive manner and only perform brief attentional shifts.

1.6.2 Visual search

Visual search tasks typically involve the presentation of different static items and participants are required to visually search for targets amongst distractors (Wolfe, 2015). Examples include searching for Ts amongst Ls (Wolfe & DiMase, 2003), searching for red shapes among green shapes (Daoutis et al., 2006; Treisman & Gormican, 1988) searching for happy faces among sad faces (Hickey et al., 2010), and so forth. In order to serve as an adaptive behaviour, visual search is typically biased towards relevant information while suppressing the irrelevant ones in order to facilitate target detection (Corbetta & Shulman, 2002). Allocation of attention in any visual search is usually guided by different sources of information, also referred to as target attributes (e.g. colour, shape size) which allow observers to compare the input of visual information to pre-existing mental representations of items. Successful target detection is achieved when the visual input matches the mental representation the observer holds for that item. For example, when searching for your red mug in the kitchen, you are using attributes of shape, colour and size to identify the item in your visual field which matches your mental representation of the mug (more details on the different factors guiding attention allocation are given in section 1.7 of this thesis).

Visual search tasks are widely used in different variations to investigate attention allocation and attention capture. More common are manipulations of set size and stimulus complexity (e.g. conjunctions versus single features). The number of targets to be searched for is often manipulated with the majority of search tasks using single- or dual-target searches (for examples see: Barrett & Zobay, 2014; Menneer et al., 2007). Notably, multiple target search, where more than two targets are searched for, are now becoming increasingly common in attention literature (Drew et al., 2017; Drew & Wolfe, 2014; Wolfe, 2012b) as they more closely resemble real-life situations where we are not simply looking for one or two targets, but for multiple targets (Ort & Olivers, 2020). It is worth making a distinction between multiple target search tasks in which participants are required to simultaneously look for multiple targets in a given display (Drew & Wolfe, 2014) and hybrid search tasks in which participants are required to perform a visual search for an instance of any of several possible targets held in memory (Schneider & Shiffrin, 1977; Wolfe, 2012a). Alternatively, visual search tasks can vary in stimulus complexity in regards to the type of search the observer will be performing, whether this will involve searching for distinct targets (i.e. target search) or searching for whole categories (i.e. categorical search; Kristjánsson & Kristjánsson, 2018; Wu & Fu, 2017).

1.7 Guidance of attention allocation

After outlining the two experimental paradigms of MOT and visual search in their traditional versions, it is important to explain how these paradigms are modified in the current thesis to meet the aims and objectives. As already stated in section 1.5, in the current piece of work, unequal attention prioritisation of different targets and spatial regions is investigated in both dynamic (Chapters 2 and 3) and static (Chapter 4) contexts to explore the efficiency of attention allocation to multiple targets of different importance and the nature of our attentional resource. In all seven experiments of this thesis, this investigation is done through the top-down manipulation of 'priority' which is expected to guide attention allocation of participants. In particular, participants are given top-down instructions about priorities of different targets or spatial regions. This is expected to lead to prioritisation of high priority targets and regions over low priority ones (i.e. unequal attention allocation). Priority of targets or regions is expressed either as *probability* of appearance or as associated *reward value* which are both expected to lead to the high priority targets or regions being viewed as more important to attend than the low priority ones. These assumptions and predictions are based on findings in the literature looking at different forms of *guidance* during attention allocation (see Guided Search 6.0; Wolfe, 2021), with the main ones including top-down (i.e. endogenous) and bottom-up (i.e. exogenous) influences.

1.7.1 Top-down and bottom-up influence

Top-down influences refer to internal behavioural goals of the agent who is completing the task (i.e. endogenous and voluntary influences) which can also be related to specific task demands and instructions; while the latter is concerned with the physical saliency of targets (i.e. exogenous and involuntary influences; Duncan & Humphreys, 1989; Pashler et al., 2001). The expectations and knowledge an observer has, as well as the mental representations of different targets, constitute of top-down influences during attention allocation. The more the similarities between targets in the visual field and mental representations of an item, the quicker and more effective attention allocation will be (Ristic et al., 2006). Top-down information can also guide our attention in a goal-directed manner to specific information that is relevant to our thoughts, feelings, intentions or requirements of a task we are completing (Buschman & Miller, 2014; Crowe et al., 2019).

Alternatively, bottom-up influence on attention allocation and visual search are primarily stimuli-driven and are related to saliency of items' features as well as their similarity with distractors. Different stimuli features that can guide attention allocation in a bottom-up manner include brighter colours, larger target size and orientation etc. (Wolfe & Horowitz, 2017; Wolfe & Horowitz, 2004). Attention allocation and visual guidance to a target is generally stronger when there are large differences between target and distractors and small differences between distractors (Duncan & Humphreys, 1989; Wolfe, 2021). For instance, Theeuwes (1991; 1992; 1994) found that observers' visual search performance for a specific target (e.g. searching for a triangle among squares) was compromised if a highly salient distractor (e.g. red square among otherwise black items) was presented. These findings indicate how bottom-up factors like perceptibility or saliency of items can guide participants' attention even to irrelevant stimuli. Similarly, van Zoest and Donk (2004) found that participants' responses when searching for vertical line segment (i.e. the target) among tilted line segments (i.e. distractors) were slower when the distractor was of higher saliency than the target, illustrating the impact of bottom-up target features on attention allocation.

Evidence suggests that top-down and bottom-up influences on attention allocation are not independent of each other. In particular, research shows that at the initial intake of information, we are primarily impacted by bottom-up factors yet this dominance decreases with time and after the initial, feedforward sweep of information, top-down influences come into play and our attention is primarily guided by individual goals and intentions (Van der Stigchel et al., 2009). What is more, the extent to which bottom-up information will impact attention allocation also depends on observer's expectancy and expertise (Hershler & Hochstein, 2009). For example, when you are searching for your white mug (i.e. the target) on the table, you are less likely to be influenced by the presence of a red vase (i.e. a distractor more salient than the target) if you are already aware it is there. What is also important to note is that top-down and bottom-up factors are not the only influence on attention allocation as other factors are important as well. More specifically, prior history of recent attentional deployments can lead to selection biases (Awh et al., 2012; Wolfe 2021). For example, Maljkovic and Nakayama (1994) showed that repetitive exposure to red targets on previous trials increased the speed and accuracy of responses to red targets in subsequent trials, what is also referred to in the literature as priming effects. Similarly, scene semantics can also impact attention allocation irrespective of top-down and bottom-up influences (Wolfe, 2021). For instance, Boettcher et al., (2018) indicated that during attention allocation in real-life settings, some 'anchor objects' in the scene can be used to facilitate detection of the target items. For example, if you are searching for your toothbrush in the bathroom you search can be facilitated if you first locate the sink.

1.7.2 Value

Another form of guidance of attention allocation is value or importance associated with different targets, features or even whole regions of our visual field (Kiss et al., 2009; Krebs et al., 2010; Serences, 2008; Gong et al., 2016). The amount of attention allocated to an item increases when it is associated with a reward, while it decreases when it is associated with a punishment (Anderson et al., 2011b; Anderson & Yantis, 2012). The beneficial effects of value on visual search performance and attention allocation have been demonstrated in cases where distinct target features are rewarded in simple visual search tasks with different shapes (Hickey et al., 2011; Laurent et al., 2015) but also in experimental tasks with real-life settings as well (Hickey et al., 2015). Additionally, Lee and Shomstein (2014) specified that value can entirely guide attention to a target and not simply increase the observer's response to it only after it is found, further denoting the strong impact of value on attention allocation and visual search performance.

Value can modulate attention allocation and visual search performance in both a top-down and a bottom-up manner. The former case has been observed when some items or targets were explicitly associated with a higher priority (probability of occurrence or reward; (Libera & Chelazzi, 2006; Navalpakkam et al., 2010; Shomstein & Johnson, 2013). The latter case is evident when high value of targets on previous trials exerts some pop-out effects for those targets in subsequent trials and more attention is attracted on them in a bottom-up manner even if on the subsequent trials those targets are no longer the high priority ones (Kiss et al., 2009; Kristjánsson et al., 2010).

1.8 *Aims of thesis*

The aim of the current thesis is to investigate unequal attention prioritisation of different targets or spatial regions. This will be done through the manipulation of 'priority' which will take different forms (i.e. either *probability of occurrence* or *associated reward* will be manipulated) and levels (i.e. low, medium and high). This manipulation of 'priority' is expected to lead to goal-directed unequal attention prioritisation of different targets or regions of the visual field depending on the different levels of their associated priorities. The concept of 'priority' manipulation during attention allocation largely stems from the work of Fecteau & Munoz (2006) who recommend the term 'priority map' to argue that the combination of top-down and bottom-up influences on attention create an amalgamated representation of *priority* which refers to the combination of an object's bottom-up distinctiveness and its relevance to the observers. According to this approach, priority as the representation of both salience and relevance, best describes how attention is allocated in a given visual scene and the firing properties of neurones in our oculomotor system.

In the case of the current thesis, in Experiment 1 (Chapter 2), the priority of targets indicated their likelihood of being probed at the termination of the trial. In Experiments 2 and 3 (Chapter 3), priority is not associated with individual targets but with different regions of the visual field and it indicates the likelihood that a target will be questioned in each of the regions, at the end of the trial in a modified MOT task. Finally, in Experiments 4-7 (Chapter 4) priority of different static targets represents either the prevalence (i.e. likelihood of appearance) or the reward associated with each target in a hybrid search task.

The current thesis constitutes of an investigation of unequal attention prioritisation of different targets or regions of the visual field through the manipulation of their priority, in the context of both moving (i.e. MOT) and static (i.e. visual search) items. It is worth noting that important differences exist between attention allocation in moving versus static contexts. For example, motion processing required during MOT increases attentional demands of the task decreasing the number of items which can be simultaneously processed, compared to static visual search settings (Flombaum & Scholl, 2007). Furthermore, attention prioritization of *multiple* targets differs in moving and static contexts as well, particularly in the case of the tasks used in the current thesis. In current MOT task (Chapter 2 and 3), multiple target are presented during a trial and participants are required to dynamically allocate their attention them, prioritizing tracking of some versus others (based on the associated priority of targets themselves or of their regions). To the contrary, in the current hybrid search task (Chapter 4), only one static target is present in a given trial yet participants are required to visually search for three static items held in their memory (as they are not aware which of the three will be presented) and prioritise search for some of those versus others (based on their associated priority). In spite of the differences between communalities of MOT and visual search, it is important to investigate the process of attention allocation using different paradigms in order to investigate different sub-processes of attention which might be involved in different tasks (Rensink 2009; 2013; 2015; for more discussion on tis approach see section 5.3). This allows for a more holistic investigation of visual attention and for more conclusive inferences to be drawn.

The main aim of this thesis across all empirical chapters is to explore *participants' ability to allocate their attention to multiple targets*: Do participants solely focus on the high priority target and completely neglect the others or would they allocate attention to multiple targets? If the latter would be the case, do participants allocate their attention to targets in a graded manner based on their assigned priority or do they have similar degrees of accuracy across all priority conditions? These are all questions which this thesis aims to address in order to investigate how effectively observers can divide their attention unequally to different targets or regions of the visual field. While equal attention allocation has largely been investigated, little work has been done on *unequal* attention division and the insights this process can offer regarding the architectural structure of our attentional resource (i.e. fixed vs flexible).

Although unequal attention prioritisation of multiple targets and spatial regions is the main investigation of this thesis, some related topics are explored. In particular, Chapter 3 explores the importance of overt and covert vision during unequal attention allocation (relevant literature will be reviewed in section 3.2). In addition, Chapter 4 explores a perceptual bias referred to in the literature of the prevalence effect (i.e. detecting with less efficiency targets which are rarely present in our visual field). In particular, experiments in Chapter 4 explore the possibility of eliminating prevalence effect through the manipulation of unequal reward (i.e. as the prevalence associated with a target increased, the reward associated with its accurate detection decreased) to increase participants' vigilance to low prevalence targets (relevant literature for this will be reviewed in section 4.2).

The findings reported in the current thesis will also be discussed in relation to their practical implications regarding unequal attention allocation in real-life settings (e.g. sports playing, driving) and in relation to their theoretical implications for the structure of our attentional resource (i.e. fixed vs flexible) and the potential sub-processes involved during allocation of visual attention.

1.9 Overview of Experimental Chapters

1.9.1 Overview of Chapter 2

Chapter 2 investigated unequal attention prioritisation of individual moving targets in a modified multiple object tracking task where individual targets were probed with three different levels of priority (i.e. low, equal and high). Eye movements of participants during tracking were recorded. Findings indicated that as the priority of a target increased, participants' tracking accuracy (for direction of heading judgements) improved in a graded manner while they also looked at or near it and for a larger proportion of time. The findings provide evidence for unequal attention prioritisation of targets as both perceptual performance measures and gaze measures suggest that participants are able to prioritise tracking of high priority targets but do not completely neglect low priority targets. These results provide support for a flexible deployment of attention resources which can be allocated unevenly to different targets in a demand-based manner.

1.9.2 Overview of Chapter 3

Chapter 3 explored unequal attention prioritisation of different regions of the visual field in a modified multiple object tracking task where different regions (i.e. top vs bottom, left vs right) were probed with different priorities (i.e. low, equal, high). Eye movements of participants were again recorded. Results of Experiment 2 indicated that participants allocated their attention to the different regions in a graded manner denoted by the improved tracking accuracy (for direction of heading judgements) and more frequent and prolonged eye gaze in that region as priority increased. Experiment 3 aimed to explore the role of eye movements in unequal attention allocation and therefore, participants performed the task using either overt (i.e. foveal) or covert (i.e. peripheral) vision. Findings indicated that eye movements were functional in that they slightly improved accuracy when participants could freely move their eyes compared to when they had to fixate centrally. Additionally, replicating Experiment 2, better tracking performance was found for high compared to low priority regions, in both the free and fixed viewing conditions, but the benefit was greater for the free viewing condition. Although unequal attention allocation is possible without eye movements, eye movements seem to improve tracking ability, presumably by allowing participants to fixate more in the high priority region and get a better, foveal view of the objects. These findings can help us better understand how observers in real-life settings (e.g. CCTV monitoring, driving) can use their limited attentional capacity to allocate their attention unequally in a demand-based manner across different tracking regions.

1.9.3 Overview of Chapter 4

Chapter 4 studied unequal attention prioritisation of individual static targets in a hybrid search task where different items were associated with different levels (i.e. low, middle, high) of priority (i.e. prevalence and/or reward). Results indicated that as priority of targets increased, whether this was through a manipulation of prevalence (Experiment 4) or reward (Experiment 5) participants' reaction time and accuracy during visual search improved in a graded manner. Additionally, this chapter was concerned with the prevalence effect which refers to the bias of detecting with less efficiency targets which are rarely present in our visual field (e.g. tumours in X-rays; dangerous items in airport security screenings). Although some studies have attempted to eliminate this effect, most of these studies use *single*-target searches. In Experiments 6 and 7 of the current Chapter, the interaction of prevalence and reward effect was explored, testing whether and to what extent the prevalence effect can be diminished, eliminated or even reversed, through the manipulation of unequal (Experiment 6) or equal (Experiment 7) reward. In Experiment 6 reward was manipulated inversely to prevalence such that as the prevalence associated with a target increased, the reward associated with it decreased. In contrast, in Experiment 7 the same reward was associated with all targets irrespective of their different prevalence levels. Results of Experiments 6 and 7 provided further support for the robustness of the prevalence effect, although unequal rewards (Experiment 6) did diminish the prevalence effect to some extent, compared to equal reward (Experiment 7). Current findings provide evidence for the flexible nature of our attentional resource while also have practical implications regarding ways in which prevalence effect can be diminished in real-life settings.

Chapter 2 Unequal attention prioritisation of individual moving targets

Work presented in this chapter is currently under preparation for submission at Journal of Experimental Psychology: Human, Perception & Performance. Apart from some minor edits, this chapter is presented as per the manuscript. VH was responsible for the experiment design, programming and set-up, data collection and analysis as well as manuscript preparation. DZ and EU were responsible for some data collection. CK and CL, as primary and secondary PhD supervisors of VH, were responsible for supervising the study.

2.1 Chapter Summary

In many common situations, we are required to allocate our attention unevenly across different moving targets that have different levels of importance. For example, when driving a car or playing sports. Investigations of attention allocation during multiple object tracking have largely been based on perceptual performance of participants without necessarily looking at the eye movements of participants during tracking. In this Chapter, the role of eye movements was directly investigated in a modified trajectory tracking task where target priority was manipulated to explore how attention is allocated between multiple moving objects. Findings indicated that as the priority of a target increased, participants' tracking accuracy (for direction of heading judgements) improved while they also looked at or near high priority targets for a larger proportion of the time compared with lower priority targets. These results provide evidence for unequal attention allocation during tracking as both perceptual performance measures and gaze measures suggest that participants are able to prioritise tracking of high priority targets but do not completely neglect low priority targets.

Findings also indicate a flexible deployment of attention resources which can be allocated unevenly to different targets in a top-down, demand-based, manner. These findings are also discussed with respect to their usefulness for understanding how people in different real-life settings allocate their attention unequally.

2.2 Introduction

2.2.1 Multiple Object Tracking

In many everyday tasks, people are required to allocate their attention simultaneously to different individual objects. Further, in many instances, targets are moving objects. Common instances include playing sports (e.g., tracking different players and the ball, for example in a game of football), CCTV monitoring (e.g., tracking potential criminals), driving (e.g., tracking other road users and pedestrians) and video games (e.g. first person shooters). As has been described in Chapter 1, the MOT task, first developed by Pylyshyn and Storm (1988) is very often used to investigate division of visual attention across multiple dynamic targets. They allow for an ecologically valid way to investigate how attention is allocated during tracking of multiple moving targets in different real-life settings (Scholl, 2009).

Investigating factors that influence tracking performance in MOT tasks offers important insights into the capacity and structure of our attentional resource. For instance, tracking performance on MOT tasks can be compromised when attentional demands of the task increase, for example when targets move at higher speed (Alvarez & Franconeri, 2007; Intriligator & Cavanagh, 2001; Scholl et al., 2001), when the proximity of objects is closer (Franconeri et al., 2008; Tombu & Seiffert, 2008), when targets are smaller (Bettencourt & Somers, 2009), when targets appear in the same hemifield (Alvarez & Cavanagh, 2005), or when the set size is increased (Drew et al., 2011; Yantis, 1992). During MOT tasks, participants are generally able to track approximately four objects simultaneously, however this number can increase to eight, and possibly beyond, at slower movement speeds (Alvarez & Franconeri, 2007). Increasing the number of items decreases the inter-object spacing resulting in crowding, which has been found to have a critical role in decreasing tracking performance (Franconeri et al., 2008; Intriligator & Cavanagh, 2001).

2.2.2 Theoretical accounts of attention

The limitations in the tracking performance of participants in MOT tasks indicate a finite attentional resource as tracking accuracy for any single object generally decreases with an increasing tracking load. Different theoretical frameworks have been proposed to explain the structure of this attentional resource, with different authors arguing in favour of either a fixed or a flexible architectural system (for detailed review see: Meyerhoff et al., 2017).

2.2.2.1 Fixed theories

Fixed theories of attention allocation argue in favour of a limited attention resource that is allocated to different to be tracked objects in the same manner irrespective of their potentially unique properties or identities. For example, Visual Index Theory (Pylyshyn, 1989; 2001; 2007) also referred to as the Fingers of Instantiation (FINST) model, argues in favour of a fixed number (i.e. around 4) of visual indexes (i.e. FINSTS) which are allocated to objects during tracking and match the visual input to cognitive representations. According to this approach, attention allocation is preconceptual as these visual slots are allocated to items during motion in an automatic manner, without encoding any information about their individual identities or properties. Findings of studies beyond the MOT literature provide support for this theory, including visual search and subitizing investigations (Pylyshyn et al., 1994) denoting that attentional capacity is indeed limited to around four items which is indicative of an attentional resource of fixed architectural structure.

Yantis (1992) developed another fixed theoretical model for attention allocation, namely the Perceptual Grouping Model, according to which individual targets are grouped by our visual system into a higher order visual representation which is maintained during tracking (e.g. three single items being connected to form a triangle). According to this notion, participants track the centroid location of this larger visual representation and in this way maintain knowledge of individual target locations. Evidence to support this theoretical approach has been obtained by studies highlighting the importance of the centroid of targets during tracking. For example, in a series of MOT experiments, Alvarez and Oliva (2008) showed that even if attention was withdrawn from individual targets during tracking, attention to the centroid location of the targets remained above chance level, providing evidence of the notion of perceptual grouping of individual targets into a larger visual representation during tracking.

Similarly, another fixed theory of attention allocation, is the Multifocal Theory (Cavanagh & Alvarez, 2005; McMains & Somers, 2004; Müller et al., 2003). This approach argues for the existence of multiple foci of attention (which have a similar role as the visual slots or FINSTS described by the Visual Index Theory) which are allocated to objects being tracked and provide continuous attentional access. Empirical support for this theoretical framework stems from findings on attentional independence across the two hemispheres during tracking (Chen et al., 2013; Hudson et al., 2012). In particular, Alvarez and Cavanagh

(2005) found that the number of objects which participants were able to track doubled when these were divided across the two hemispheres, left and right, indicating that there is a distinct attentional resource for tracking in each hemisphere. These findings provide evidence against a single focus of attention proposed by the Perceptual Grouping Model and rather shows that attentional focus can be split between different regions.

2.2.2.2 Flexible theories

Flexible theories argue in favour of a continuous pool of attentional resource that underlies tracking of multiple moving objects and allows for more attentional resource to be devoted to some targets over others. For instance, the FLEX model proposed by Alvarez and Franconeri (2007) assumes that objects are tracked by flexibly allocated indexes (i.e. FLEXes), the total number of which is limited by the finite attentional resource (Alvarez et al., 2005). According to this mode, attention allocation can dynamically change during tracking depending on task demands and difficulty levels (e.g. variations in speed and target proximity). Evidence supporting this demand-based allocation of attentional resource is provided by Iordanescu et al. (2009) who found that participants allocated more attentional resources to targets which were at risk of being lost during tracking because they were in close proximity to distractors versus targets who were not close to distractors. These findings indicate a demand-based dynamic distribution of attention during tracking.

Similarly, Franconeri et al. (2010) developed the FLEX model even further and suggested the Spatial Interference Theory of MOT which argues that the pool of our attentional resource is flexibly allocated to different targets based on their location in order to aid tracking. In particular, attentional enhancement is flexibly allocated to targets when they are close to distractors, forming an inhibitory surround. According to this model, tracking errors arise when distractors break through this inhibitory surround of targets and therefore according to this approach close proximity of targets with distractors is seen as the only limiting factor of MOT performance. Supporting evidence for this theory comes from findings of both Franconeri et al. (2008) and Franconeri et al. (2010) showing that object spacing is the origin of all performance limitations during MOT and if that stays constant tracking performance is not significantly affected by changes in speed and number of items.

2.2.3 Eye-movement strategies

While the majority of the aforementioned theoretical frameworks on the structure and capacity of our attentional resource have been based on the perceptual performance of participants in MOT tasks, it is important to note that gaze measures provide us with an important insight into the process of attention allocation as well and allow us to draw more conclusive inferences. In particular, gaze measures from MOT studies have led to the identification of different eye-movement strategies employed by observers during attention allocation (Fehd & Seiffert, 2008, 2010; Zelinsky & Neider, 2008). For instance, according to the target-looking strategy participants may track targets individually and continuously saccade from one target to another, so that each target is viewed with high visual acuity (Zelinsky & Neider, 2008). Landry et al., (2001) investigated the eye movements of participants when they monitored objects for potential collisions, during a simulated air-traffic control tracking task. More frequent saccades were observed when participants monitored targets on a potential collision, versus when they monitored other targets that were not likely to collide. This evidence indicates that observers tend to fixate on items when tracking gets difficult, suggesting that making eye movements to targets facilitates attentional tracking performance as saccades can allow for a foveal view of objects that can aid in updating their position (Hoffman & Subramaniam, 1995; Shepherd et al., 1986).

Alternatively, Fehd and Seiffert (2008, 2010) proposed the centroid-looking strategy according to which participants mentally group multiple targets into a single polygon and track that shape as a whole by looking at its centre. This strategy suggests that what we fixate is not necessarily what we attend to, indicating that we can also attend to targets with our peripheral vision using covert attention (Linnell & Humphreys, 2004). It has been found that task-relevant stimuli can be detected and processed when they appear both inside (i.e. overt attention) and outside (i.e. covert attention) the fixation region (Lichtenstein-Vidne et al., 2007). Looking at the centre of a target array can minimize the eccentricity of each of the targets. This can help participants individuate peripheral targets from distractors and hence, aid tracking performance (Huff et al., 2009, 2010; Intriligator & Cavanagh, 2001; Liu et al., 2005; Seiffert, 2005). Zelinsky and Neider (2008) investigated eye movement strategies during MOT in a 3D computerised MOT task where observers were required to track sharks in an underwater scene. The centroid strategy was found to be beneficial for tracking performance as it yielded higher tracking accuracy when employed, compared to switching eye gaze between targets which decreased tracking ability, supporting the findings of Fehd and Seiffert (2008, 2010). It is worth noting however that participants employed the centroid strategy only at low visual loads (i.e. 2-3 targets) and switched to a target-looking strategy for higher visual loads (i.e. 4-5 targets). These findings indicate a clear load-dependency of the tracking strategy. The centroid-looking strategy is consistent with the Multi-focal account of attentional tracking which allows for continuous attentional access for all objects being tracked (Allen et al., 2004, 2006; Cavanagh & Alvarez, 2005), while it is also consistent with aspects of the Perceptual Grouping Model proposed by Yantis (1992), according to which the visual system groups individual targets into a shape (i.e. triangle or quadrangle) which constitutes a higher order visual representation.

2.2.4 Allocating attention unequally during tracking of multiple moving objects

It is worth noting that the theories regarding the structure of our attentional resource (i.e. fixed versus flexible) and the eye movement strategies we employ during tracking (i.e. target-looking versus centroid-looking) are primarily based on traditional MOT tasks in which participants divide their attention *equally* between different targets. Nevertheless, this is unlike many real-life settings where individuals have to track objects with different levels of importance and hence, have to allocate their attention unequally to the different targets. For instance, during driving we are required to divide our attention unevenly between targets of greater importance (e.g. other vehicles, pedestrians) and targets of less yet not completely negligible importance (e.g. road signs).

In the MOT context, evidence for participants' ability to allocate their attention unequally to different targets has indirectly been provided from studies manipulating objects' speed (Chen et al., 2013; Liu et al., 2005) or proximity (Iordanescu et al., 2009; Meyerhoff et al., 2016). For instance, Liu et al, (2005) manipulated the speed of objects in a classic MOT task, such that half of the objects moved at a fast speed of 6° per second and the other half at a slow speed of 1° per second. Higher speed of targets increases tracking load and as a result, participants had to allocate more attention to these targets to successfully track them (Alvarez & Franconeri, 2007; Intriligator & Cavanagh, 2001; Scholl et al., 2001). Nevertheless, findings indicated similar tracking performance across both slow- and fast-moving objects.

This is indicative of unequal attention allocation, as in order for similar tracking accuracy to be observed between fast- and slow-moving targets, it means that more attention was allocated to the former to compensate for their increased tracking demands. Unequal attention allocation is thought to facilitate tracking of targets which are at risk of being lost due to their close proximity with distractors (Meyerhoff et al., 2016; Meyerhoff et al., 2018). When inter-object spacing between targets and distractors was manipulated, participants were found to allocate more attention to the crowded targets (i.e. targets with the shortest distance from distractors) which were more at risk of being confused with distractors, compared to the uncrowded ones (Iordanescu et al., 2009).

Evidence for unequal attention allocation has also been reported in studies that directly manipulated the *priority* of targets or of certain features of the targets (e.g. location, identity, colour) and participants were required to unevenly divide their attention in a goal-directed manner, prioritising the search or tracking of the high priority targets or features versus the low priority ones (Fitousi, 2016; Miller & Bonnel, 1994). For instance, Cohen et al. (2011) modified a traditional Multiple Identity Tracking (MIT) task, which involves tracking objects of unique identity (Oksama & Hyönä, 2008), and they asked participants to prioritize tracking of either location or identity of targets. Findings indicated better position- versus identity-tracking performance when participants were asked to track the position of targets and better identity- versus position-tracking performance when they were asked to track the identity of target. These results support goal-directed, unequal attention allocation to different features (location or identity) of the same object.

Crowe et al., (2019) provided evidence for top-down strategic unequal attention allocation. They examined the effect of the priority of targets on participants' magnitude of error in a modified trajectory-tracking MOT task in which participants' task was to track two targets amongst distractors and then determine the direction that one of these two targets (i.e. the queried target) was moving in, unlike classic MOT tasks where participants are questioned about status of an item (i.e. whether it was a target or distractor). Target priority was manipulated as percentages denoting the likelihood of each of the two target being questioned (e.g. 25% and 75%; 50% and 50%), signalled at the start of the trial. Participants allocated more attention, indexed by higher tracking accuracy, to targets that were associated with a higher probability of being probed versus those that were associated with a lower probability of being probed. A mixture distribution analysis also indicated that as priority of targets increased, participants' tracking precision increased and proportion of guessing decreased. These findings indicate that observers can indeed decide to allocate their attention unequally based on the task demands and top-down instructions, in a goal-directed manner. However, in this study conclusions for unequal attention allocation were drawn solely from findings on perceptual performance of participants as no direct measures of attention were taken.

It is important to investigate goal-directed unequal attention allocation through direct measures of attention (e.g. through eye-tracking) in order to make stronger inferences about how overt attention is allocated to multiple moving targets with varied priorities during a trial. What is the distance of participants' eye gaze from the high and low priority target throughout the trial? How much proportion of participants' time is devoted looking at the high priority target and how much at the low priority target? These are questions which can be answered if eye movements of participants are recorded during a MOT task, providing stronger evidence for unequal attention prioritisation.

2.2.5 *Aims of Chapter 2*

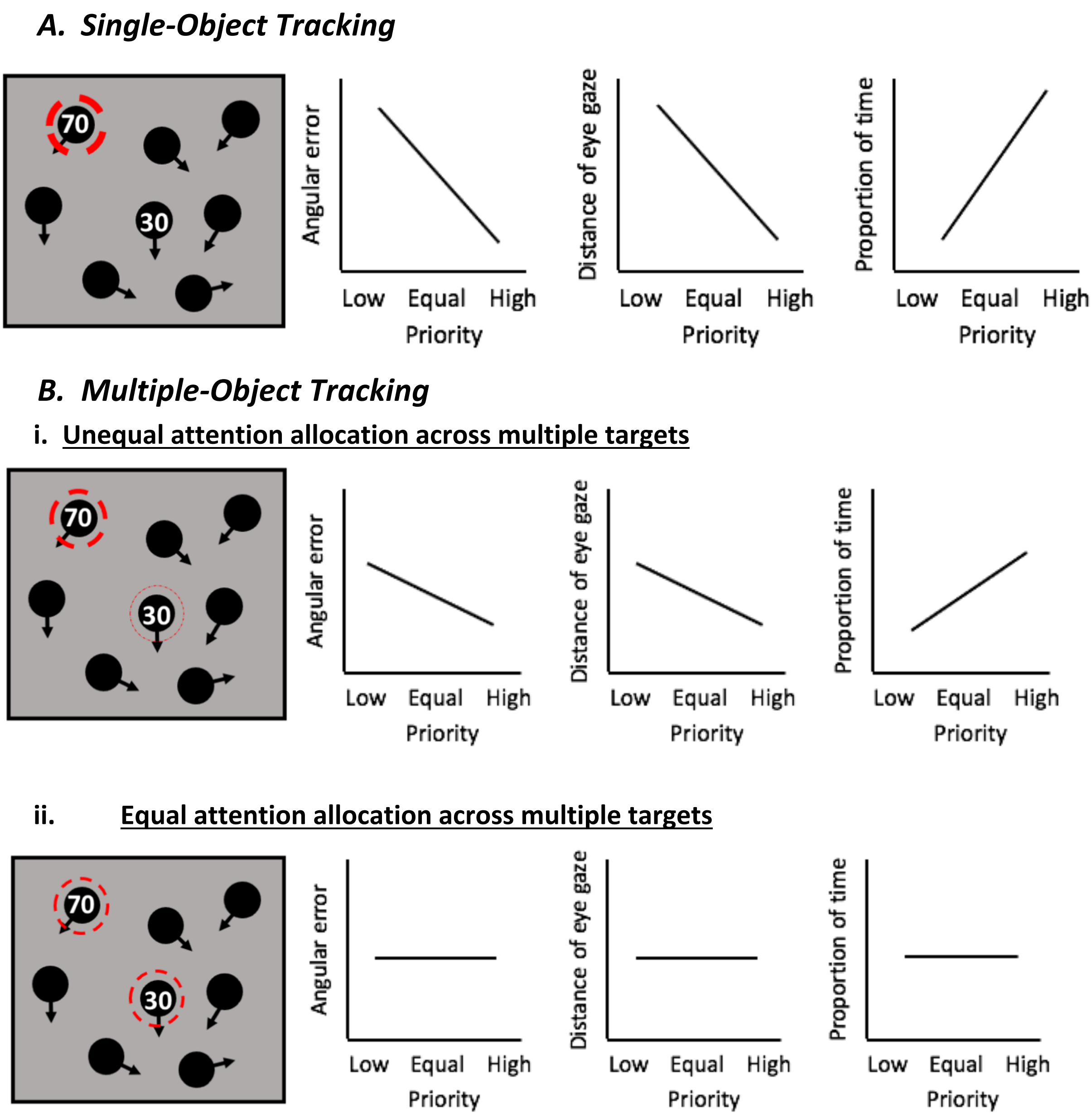
The aim of this Chapter was to investigate unequal attention prioritisation of different targets by manipulating target priority, while recording eye movements of participants to gain insights into participants' tracking behaviour and attention allocation during a trial. This constitutes of one of the first investigations on unequal attention allocation using eye movements as past investigations were primarily based on perceptual performance (i.e. Crowe et al., 2019; Oksama & Hyönä, 2008). The current experiment is therefore expected to offer an important insight and provide direct evidence for unequal attention allocation through the investigation of eye movements of participants and an exploration of how these are allocated across targets during tracking. Closely replicating Crowe et al. (2019), a trajectory-tracking MOT task was used in which target priority was manipulated at three levels (i.e. low: 30%, equal: 50% and high: 70%), with this denoting the probability that participants would be questioned about trajectory of each target. Participants had to track two targets amongst visually identical distractors. To my knowledge, no similar investigation exists as all past MOT studies conducted with eye movement recording relied on equal attention allocation.

Different possible outcomes exist regarding the behaviour of participants during the task of the current Chapter. The most important ones are outlined in Figure 2. According to Prediction A, participants would perform single-object tracking, devoting all their attention to one of the two targets, presumably the high priority one. This would result in large differences in participants' perceptual performance and gaze measures across priority conditions (represented in Figure 2, Panel A as steep slopes). In particular, high tracking performance (i.e. minimal angular error) for the high-priority target and below-chance tracking performance (i.e. very high angular error) for the low priority would be expected. Similarly, all eye gaze would be devoted to the high priority target (i.e. very small distance of eye gaze from high priority target and very high proportion of time) and minimal gaze would be devoted to the low priority target (i.e. very high distance of eye faze from the low priority target and very low proportion of time).

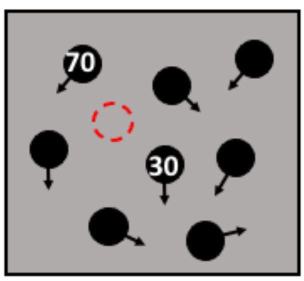
Alternatively, according to Prediction B participants are expected to perform multiple object tracking. This prediction covers two different possibilities: based on Prediction Bi, participants will perform unequal attention allocation across multiple targets based on their assigned priorities. This would result in less, yet significant differences, in perceptual performance and gaze measures across priority conditions (represented in Figure 2, Panel Bi as less steep slopes compared to prediction A). In particular, participants are expected to have better tracking performance on the high priority target (i.e. lower angular error) and worse, yet still above chance, tracking performance on the low priority target (i.e. higher angular error), denoting unequal attention allocation. Similarly, as priority of a target increases, distance of eye gaze from it is expected to decrease and proportion of time spent looking at it is expected to increase, indicating that participants primarily look at the high priority target but do not completely neglect the low priority target. This behaviour would be aligned with the principles of probability matching which is a phenomenon where subjects match their behaviour and performance on a task with the probability of occurrence of an event or the probability of reward (Erev & Barron, 2005; Vulkan, 2000). For instance, if two visual stimuli were associated with two different sources of reward such that option A would be rewarded 70% of the times and option B would be rewarded 30% of the times, then according to the strategy of probability matching the subject would choose option A on 70% of the occasions and option B on 30% of the occasions, even if the optimal strategy would be to constantly choose option A which is always rewarded. This matching law was first introduced in Herrnstein's (1961) experiment where he used a Skinner's box to feed pigeons at different time intervals. Pigeons were presented with two buttons to press, each of which led to different rates of food reward. After some period, pigeons developed a probability matching technique and exhibited more button presses for the button which yielded food more often than for the button which yielded food less often. Additionally, the ratio of their press rates for each button matched the ratio for the rates of reward associated with each button. In the context of attention research this would mean that participants divide their attentional resource in proportion to the probabilities of occurrence or reward associated with each target or location(Eriksen & Yeh, 1985; Jonides, 1980) which is essentially what is expected according to Prediction Bi in the current experiment. To the contrary, if evidence on favour of Prediction Bii is found, the participants would perform multiple object tracking but will allocate the same proportion of their attention to all targets irrespective of their associated priorities. This would result in flat slopes (Figure 2, Panel Bii) across all priority conditions in terms of both perceptual performance (i.e. angular error) and gaze measures (i.e. distance of eye gaze from the target and proportion of time spent looking at it).

Otherwise, Prediction C supports that participants would not track individual targets but their midpoint location. No specific predictions can be made regarding perceptual performance of participants in this scenario as this depends on the extent to which attention can be divided unequally using peripheral vision (see Chapter 3, Experiment 3 for an investigation on this). Regarding eye movements, higher amount of eye gaze would be devoted to the midpoint location of the two targets rather than to the two targets individually.

Depending on the pattern of results observed by both perceptual performance measures and gaze measures, evidence for different theories of attention allocation and eye movement strategies could be provided. Additionally, whether the observed effect will be evident across trials or within trials will also be explored. For example, if evidence is provided in favour of Prediction Bi regarding unequal attention allocation across targets based on their associated priority, then it would also be important to see whether this observed behaviour of probability matching during tracking is evident only on the average performance of participants across trials or it is evident within single trials as well.



C. Tracking of midpoint location between the two targets



Perceptual Performance: No specific predictions are made regarding perceptual performance as this depends on extent to which attention can be divided unequally using peripheral vision (see Chapter 3, Experiment 3 for more on this).

Gaze measures: Higher amount of eye gaze would be devoted to the midpoint location of the two targets rather than to the two targets individually.

Figure 2. Different predictions for results of Experiment 1. Left panels offer a schematic representation for each prediction regarding participants attention allocation during tracking.

Arrows represent movement of targets. Priority numbers were not present during tracking but are placed here to indicate priority of targets. Red dotted circles represent attention focus. The thicker the circles, the more the attention allocation on that target. Right panels offer a visual representation of expected results, regarding both perceptual performance and gaze measures. Prediction A) Tracking of a single target, presumably the high priority one; Prediction Bi) Tracking of multiple targets in a graded manner, allocating more attention to a target as its priority increases; Prediction Bii) Track of multiple targets in a similar manner, allocating a similar amount of their attention to both targets irrespective of their associated priority; Prediction C) Track the midpoint location of the two targets instead of tracking distinct targets individually.

2.3 Method

Preregistration and Open Data: The protocol for this experiment was preregistered on the Open Science Framework and can be found at: https://osf.io/wx8c7/, together with the data and analysis scripts. Ethics approval was obtained from the School of Psychological Science Research Ethics Committee at the University of Bristol (10373). The study was conducted according to the revised Declaration of Helsinki (2013).

Participants. 33 individuals (24 females) with an average age of 20.3±2.8 years were recruited from the University of Bristol in exchange for course credit. A power calculation in R was performed using the SIMR package suitable for an LME design (Green & Macleod, 2016). With an effect size of priority of -0.44 (for the difference in direction of heading judgements between high and low priority conditions, derived from a pilot experiment[1]), a sample of 33 participants gives us at least 99% power of detecting a similar effect at an alpha of .05. All participants self-reported normal or corrected-to-normal vision and were aged between 16-35 years.

Design. Out of eight discs presented on each trial, two were initially identified as targets and the remaining six were distractors. The priority of the two targets was manipulated by changing the probability of a target being probed in a within-subjects design with three levels: low (30%), equal (50%) and high (70%). Angular error was the main dependent variable for measuring tracking performance and was indexed by the absolute angular difference (in degrees) between the target's *actual* direction of heading and the participants response. Higher absolute values represent greater error between estimated and actual item heading. Based on the angular error of participants, a model-based analysis was conducted to estimate the guessing rate and precision of participants' tracking (see e.g. Crowe et al. 2019; Horowitz & Cohen, 2010; Zhang & Luck, 2008). For the eye gaze measures the distance of gaze from the high and low priority targets was used. The proportion of time spent looking at or near the high and low priority targets and their midpoint location was also recorded. All gaze measures were averaged across all frame samples within each trial.

Materials. The MOT task was programmed, and run, using MATLAB (2019a, The MathWorks, Natick, MA) and Psychtoolbox (Psychtoolbox-3.0.13; www.psychtoolbox.org). Stimuli were

[1] This pilot experiment was the first experiment of my PhD in which the same trajectory tracking MOT task was used, but in which priority was manipulated incorrectly; therefore, this experiment is not included in the thesis.

presented on a PC running Linux Mint 18 Sarah. A 24-in. ViewPixx 3D Lite monitor was used, with a resolution of 1,920 x 1,080 pixels running at 120 Hz. The experiment was run on a smaller screen window of 1,200 x 900 pixels. At a viewing distance of 70 cm, the display area subtended 46.6° x 24°. In the current set-up, 1° corresponded to 45 pixels. An Eyelink 2000 (SR Research Ltd.) video-based tracker was used to track participant's eye movements at a sampling rate of 1,000 Hz. The eye tracker was calibrated at the beginning of every block of trials and sometimes within a block if required (using the in-built 9-point calibration routine). Recording terminated at the end of every block. Saccades and fixations were parsed offline using the velocity and acceleration criteria of $30°s^{-1}$ and $8000°s^{-2}$, respectively.

On every trial, eight black (RGB value: 0, 0, 0) discs with radius 1.14° of visual angle were presented on a mid-grey background (RGB value: 128,128,128). The discs moved randomly, with an elastic collision formula applied if two discs collided with each other and a reversal of velocity if a disc hit a boundary. Discs initially appeared on the screen at quasi-random locations, at least 2.53° from the boundaries and 1.52° from other discs and moved at a speed of 10° per second. The duration of movement was randomly drawn from a uniform distribution with a range of 6,000-8,000ms.

Procedure. Figure 3 illustrates the timeline of a given trial. At the beginning of the trial, the eight discs appeared on the screen and the numbers indicating two of them as the targets appeared for 3 seconds. On each trial one of the following combination of numbers was presented: On each trial, one of the targets had a priority of 30%, 50% or 70%; the other target then had the complementary priority of 70%, 50% or 30%. These numbers represented the probability of each target being queried at the end of the trial. Then the numbers disappeared and all eight discs started moving around the screen (the black arrows were not presented on the screen but are used here to represent movement). Participants were instructed to keep tracking the two targets amongst the distractors over the whole period of movement. At the end of the trial all discs disappeared except one. Participants were then asked to click on the direction they thought the queried target was heading. Participants first clicked inside the disc to activate a ‘dial’ on the disc with an arm of 1.14° extending from the disc’s centre. The initial direction of the arm was set randomly. Participants then used the mouse to move the arm in order to indicate the estimated direction of travel and submitted their answer with a second left mouse click. After participants’ response, feedback was presented on the screen. A green arrow of size 1.14° of visual angle, appeared indicating the target’s correct trajectory. The intertrial interval was a minimum of 1 second but often longer as it was dependent on the participant fixating accurately and the experimenter initiating the trial manually.

Participants were given clear instructions on what the numbers meant before starting 10 practice trials and had the opportunity to ask any questions. A total of 200 experimental trials were divided into 5 blocks of 40 trials each. Each block included the following number of each trial type: 21 trials with 70-30 where the 70 target was probed, 9 trials with 70-30 where the 30 was probed, and 10 trials with 50-50. The order of trials was randomized for each participant. The experiment lasted around 60 minutes.

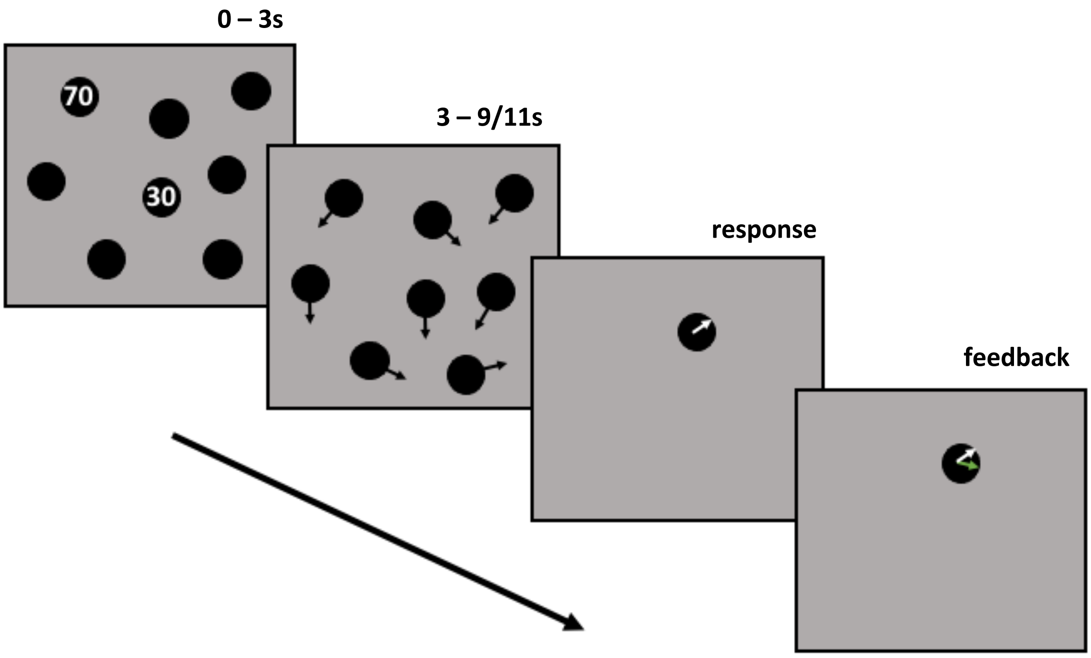


Figure 3. Trajectory tracking task trial timeline. With the commencement of each trial, the eight discs appeared on the screen and the numbers indicating two of them as the targets appeared for 3 seconds. These numbers represented the likelihood of each of the targets being “queried” at the end of the trial. These numbers were either 70-30 or 50-50. Then the numbers disappeared and all eight discs started moving around the screen (the black arrows were not presented on the screen but are used here to represent movement) for a period of 6 – 8 seconds After the period of movement all discs disappeared except one. Participants were then asked to click on the direction they believed the queried target was going. After participants’ response, feedback was presented on the screen. A green arrow appeared indicating the target’s correct trajectory.

2.4 Results

No participants were excluded from the analysis. Data was analysed using linear mixed-effects models (LMEs; (Baayen et al., 2008; Barr et al., 2013b) with the lme4 package

(Bates et al., 2015) for the R computing environment (R Core Team, 2015). Linear mixed-effects analyses were conducted with priority entered as a fixed effect and a random intercept for participant. Data for both perceptual performance and gaze measures were analysed aggregated across trials to ensure normality of data. Reported test results are the *p*-values derived from a likelihood ratio test comparing the full model, including the predictor variable of priority, to the null model which included a random intercept for subjects only, without priority included.

Planned analyses

Perceptual performance. Figure 4 indicates tracking performance of all participants individually in all three priority conditions as well as the average performance across all participants. If people gave a random response, which would be more likely in the low priority condition, we would expect an average absolute tracking error of 90°. Clearly, most participants performed better than that. Priority associated with each target had a significant effect on the magnitude of angular error, $\chi^2(1) = 31.95$, $p < .001$, whereby as the priority the target increased, the magnitude of angular error decreased, ($b = -0.35$, $SE = 0.05$, $t = -6.41$, $p < .001$).

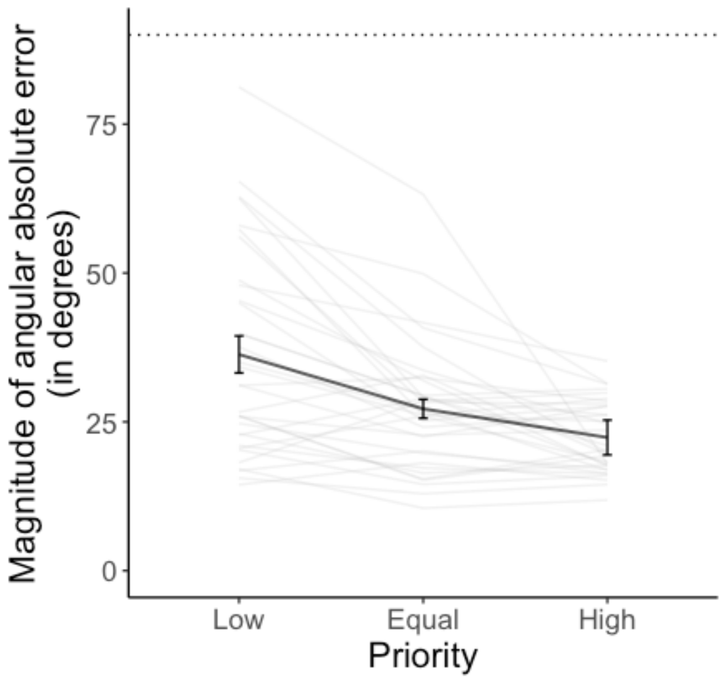


Figure 4. Magnitude of angular absolute error for each priority level. Black bold line indicates average magnitude of angular error across all 33 participants. Error bars indicate 95% confidence intervals following (Morey, 2008). Grey lines indicate magnitude of angular error for each participant individually. Dashed horizontal line indicates level of chance performance.

Following the method of Crowe et al. (2019) and Horowitz and Cohen (2010; similar to Zhang & Luck, 2008), data was further explored using a model-based analysis to investigate different possible sources which could account for the differences in the overall tracking accuracy. One possible source is proportion of guessing of participants, where guesses may be due to participants losing track of the targets or otherwise completely withdrawing attention from them. The second source is the precision of representations (due to the amount of allocated attention) of targets. A von Mises distribution (the circular equivalent of a normal distribution) centred on 0 was used to represent participants' errors when the probed item was tracked successfully. A circular uniform distribution was used to represent participants' responses when they lost track of the item and consequently guessed its direction. The MASS package (Venables, &Ripley, 2002) was used for the fitdistr function and the circular package (Agostinelli, & Lund, 2017) was used for the von Mises and circular uniform distributions functions. The uniform circular distribution, representing the situation where a participant makes a guess response, generates a random value between -180 to 180. The von Mises distribution, representing the situation where a participant has tracked a target, but to a varying degree of precision, is controlled by two parameters: μ (the mean) and κ (the concentration parameter, which determines the spread of the distribution). The mixture of guessing and tracked errors was controlled by P_G, the proportion of guessing.

Figure 5 plots the mixture model fits for error data pooled over all participants, at each of the three priority levels. The parameter P_G represents the probability of a random guess and the parameter κ represents tracking precision (the concentration of the von Mises component). The higher the κ value, the narrower the distribution around the mean, indicating higher precision (better tracking). The model fit illustrates a lower proportion of guessing and a higher precision when tracking a high versus low priority target.[2] However, similar levels of precision are observed between high and equal priority conditions, which results in the equal priority condition having both more precise tracking and more guessing compared to the high priority condition. This indicates that the model-fit parameters of proportion of guessing and precision are likely to not show a graded increasing or decreasing

[2] When a model analysis was done on individual participants, the effects of priority on the parameters of proportion of guessing and tracking precision were more fragile, presumably because more data would be needed to estimate the model parameters reliably for each participant individually.

pattern in respect to the priority of targets. The clear difference in proportion of guessing and precision between the high versus the low priority condition do follow the expected pattern (i.e. decreasing proportion of guessing and increasing precision as target priority increases) however, it could be the case that for more fine-grained differences between the low and equal priority conditions and the equal and high priority conditions more data would be required.

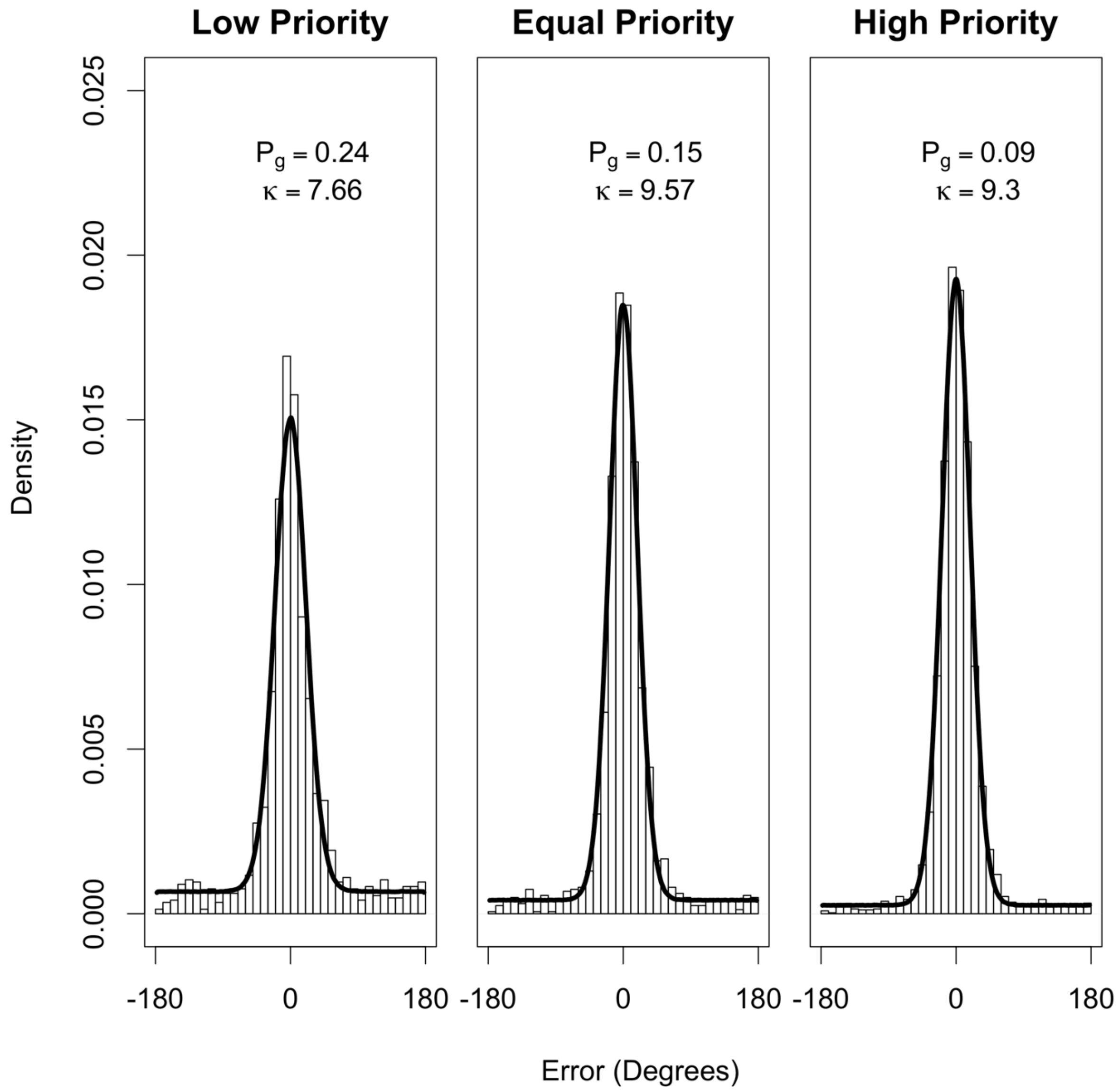


Figure 5. Fits of mixture model for the combined data across participants at each of the three priority levels; low; equal and high. The density plot illustrates actual angular error data and the black density line demonstrates the model fit. The best-fit parameters of the proportion of guessing (PG) and precision of tracking (κ) are also shown for each condition.

Gaze measures. Participants' blinks in each trial were excluded from further analysis. Two main gaze measures were calculated from the eye movement data of participants in the current experiment. The (Euclidean) distance of participants' eye gaze from the queried target (i.e. targets' centre) and the proportion of time spent looking at it. To calculate the proportion of time spent looking at the queried target, each gaze sample within a trial was classified as belonging to one of the following categories: gaze on queried target, gaze on non-queried target, gaze on targets' midpoint location, gaze on screen centre and gaze anywhere else on the screen. This classification was based on which of these locations was nearest. In addition, the fixation had to be within 2 degrees from this location. Both gaze measures were analysed aggregated across trials with LME models similar to angular error. Gaze measures regarding only the queried target were analysed and reported. Given that participants did not know which target they would be questioned on during tracking, the results on the queried and non-queried target are indistinguishable. Moreover, in this way the independence of measurements for the low, medium and high priority targets is ensured (i.e. come from different trials). Figures 6 shows the descriptive statistics (i.e. mean and confidence intervals) for distance of participants' eye gaze from the queried target (Panel A) and proportion of time spent looking at it (Panel B). Grey lines present data for each participant individually while the black bold line indicates averaged data across all participants.

The pattern of results clearly suggests that as target priority increased, average distance of participants' eye gaze the target decreased (Figure 6, Panel A). Results of the LME analysis further support this argument, there was a significant effect of priority on the average distance of participants' eye gaze from the queried target, $\chi2$ (1) = 37.03, p <.001. In particular, average distance decreased as target priority increased, b = -0.05, SE = 0.007, t = -7.05, p < .001. Similarly, as priority associated with each target increased, participants spent more time looking at that target (Figure 6, Panel B). This is further supported by the results of the LME analysis which suggest that there was a significant effect of priority on the average proportion of time participants spent looking at the queried target, $\chi2$ (1) = 36.22, p <.001. In particular, proportion of time spent looking at the queried target increased with target priority , b = 0.0034, SE = 0.00014, t = 6.95, p < .001. It is also worth noting, that the effect of priority on gaze of participants is minimal in some participants indicating that some individuals did not take the instruction of priority into consideration and allocated similar proportion of their attention to all targets. This corresponds with the analysis on the perceptual performance of participants (Figure 8) which indicates that the effect of priority was minimal or even reversed for some participants, something which is attributed to the individual differences in the way observers track multiple targets with unequal priority.

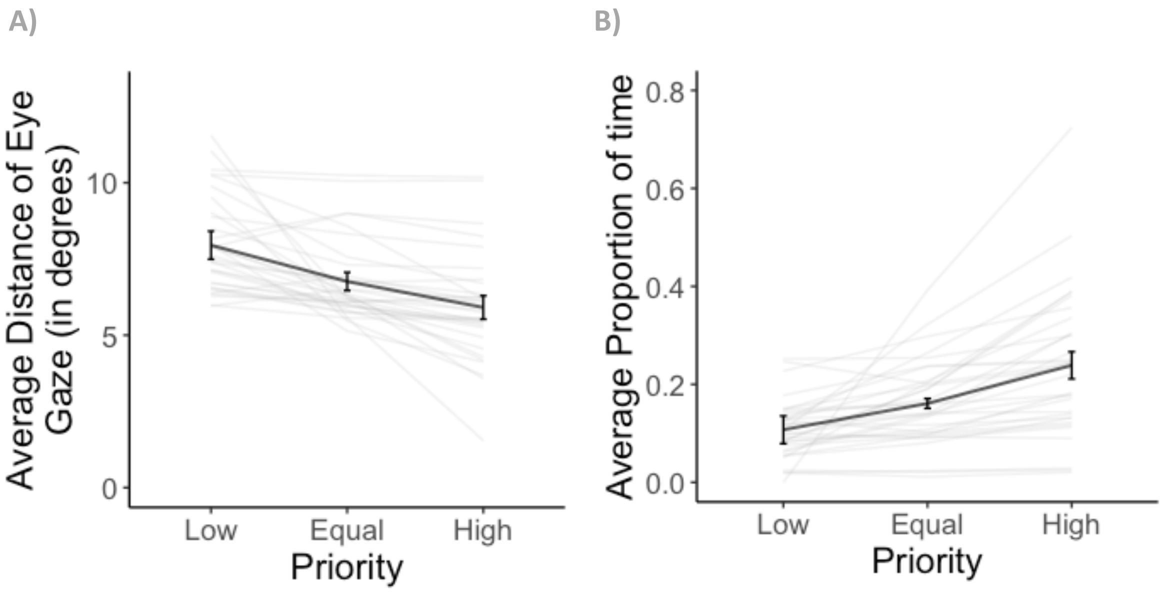


Figure 6. Average distance of eye gaze from queried target (Panel A) and proportion of time spent looking at the queried target (Panel B) in each priority condition. Black bold line indicates average data across all 33 participants. Error bars indicate 95% confidence intervals based on Morey (2008). Grey lines indicate data for each participant individually.

Interestingly, in the equal condition when both targets were probed with the same priority, the proportion of time spent looking at the queried (0.16 ± 0.18) and the non-queried

(0.16 ± 0.17) was similar to the proportion of time spent looking at the midpoint of the two targets (0.17 ± 0.15). This suggests that in the equal priority condition, participants often tracked the centroid location of the two targets as well and not only the two targets independently. When the two targets were probed with unequal priorities (i.e. low on queried target – high on non-queried; high on queried target – low on non-queried; respectively), the proportion of time spent looking at the midpoint of the two targets (0.15 ± 0.13; 0.15 ± 0.14) was less than the proportion of time looking at the high priority target (0.24 ± 0.23; 0.24 ± 0.22), yet more than the proportion of time looking at the low priority target (0.11± 0.13 ; 0.11± 0.14). This suggests that when targets were probed with unequal probabilities, participants primarily tracked the high priority target, but then prioritised the tracking of the centroid location of the two targets instead of the low priority target. This was done presumably in an attempt to not lose track completely of high priority target but also pay some attention to low priority target.

Exploratory analyses

Having demonstrated that priority influences both gaze behaviour and perceptual accuracy, it is natural to ask whether there is a link between gaze and response accuracy. Therefore, the relationship between both gaze measures regarding the queried target (i.e. average distance of eye gaze from the target and proportion of time spent looking at it) and absolute tracking error was investigated, in order to explore whether the amount of overt attention (as quantified by the two gaze measures), is associated with participants perceptual performance (i.e. absolute tracking error). The correlation for each participant on a trial level, pooled over the three priority conditions was also calculated. Figure 7 shows the distribution of these correlations for both gaze measure across participants. Panel A shows the correlations between average distance of eye gaze from the queried target and absolute tracking error that target. 88% of these correlations were positive. The mean correlation across participants of .17 was significantly different from 0, $t(32) = 6.15$, $p < .001$. This means that the more closely participants gaze was to a target the better they were at identifying its heading, with the t-statistic showing that this is indeed a robust effect. Panel B shows the correlations between the average proportion of time spent looking at the queried target and absolute tracking error for that target. 90% of these correlations were negative. The mean correlation across participants of -.14 was significantly different from 0, $t(32) = -6.21$, $p < .001$. This means that the higher the proportion of time participants spent looking at a target, the less their absolute tracking error was, with the t-statistic again showing that this is a robust effect. However, taking into account the 'cued-factor' and the idea that most or even all of the measured variables in a dataset have non-zero correlations (Tibshirani, 2014), it is important to note that although these correlations are significant, they are relatively small therefore their relevance can be questioned and hence inferences from these tests need to be interpreted with caution.

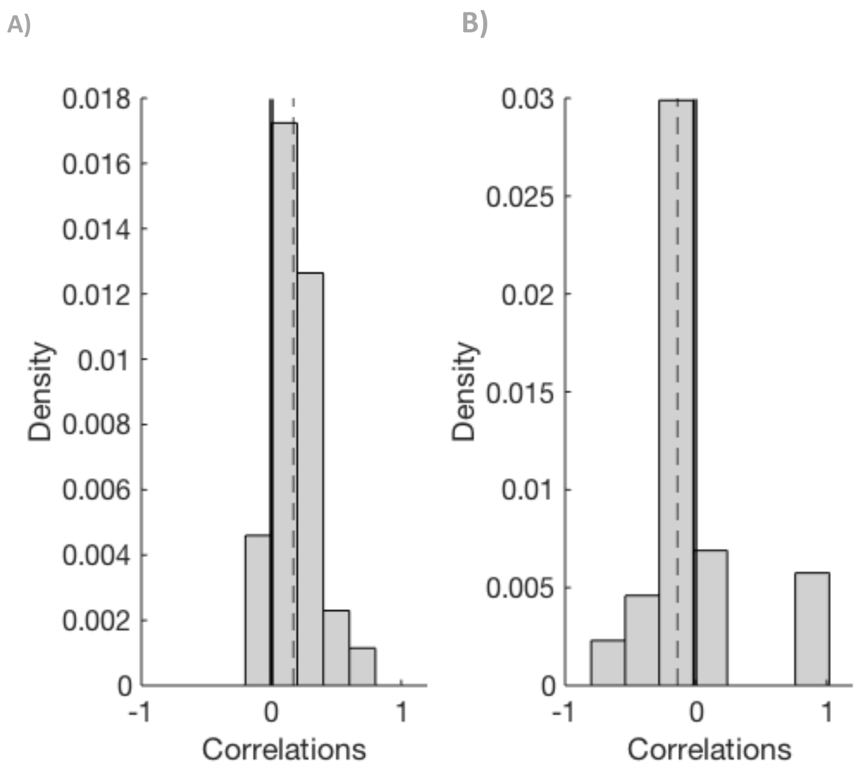


Figure 7. Histograms of correlations of individual participants. Panel A: correlations between average distance of eye gaze from queried target and average absolute tracking error for that target. Panel B: correlations between average proportion of time spent looking at the queried target and average absolute tracking error for that target. The vertical bold line indicates 0 correlation and the vertical dotted line indicates the mean of all individual correlations.

One could argue that the effect of unequal attention allocation is not evident on every trial but is a result of the data being averaged across trials. This would mean that on some trials participants completely withdrew their attention from the low priority target and tracked only the high priority target. According to this hypothesis, probability matching happened across and not within trials (Eriksen & Yeh, 1985). To assess this possibility, an additional exploratory analysis was conducted on the proportion of time spent looking at each of the two targets (i.e. queried and non-queried) *within* a trial for each priority condition. The between-trial probability matching account predicts that participants will spend almost all their time within a trial on one of the two targets: for a given combination of target and priority, the distribution of the proportion of time spent on that target should have sharp peaks near 0 *and* 1, and very little density in between these extremes—in other words, a bimodal distribution. Within-trial probability matching predicts a more unimodal distribution with data falling between these two extremes. Figure 8 shows the proportion of time spent looking in the queried target (Panels A-C) and at the non-queried target (Panels D-F). These distributions are not consistent with the bimodal pattern predicted by between-trial probability matching, but they also do not completely fit the predicted pattern for within-trial probability matching. It is likely that there is a mixture of between and within-trial probability matching, where that mixture may result from between-participant differences in strategy or variations in strategy within participants over the course of the experiment. It is evident from this analysis that proportion of time spent looking at the high priority target is not 1 (which anyway would not be the case given the division of gaze samples in the five different categories as described above) while also proportion of time spent looking at the low priority target is not 0 either. This is therefore evidence against single-object tracking and complete withdrawal of the low priority target. It also suggests that as the priority of a target increased, the proportion of time spent looking at it within each trial increased as well (yet without completely neglecting tracking of the low priority target). Also, looking at the two targets within a trial in comparison to each other (Panel A compared to Panel D; Panel C compared to Panel F), we can see that a greater proportion of time was spent looking the high priority target (Panel C and D), compared to the low priority target of that condition (Panel A and F), providing stronger evidence for unequal attention prioritisation on a trial level. Perceptual performance of participants (i.e. angular error, precision and proportion of guessing) shows that they allocated a sufficient amount of attention to high, equal low priority targets (better performance was observed as target priority increased suggesting that attention was unequally allocated based associated priority) such that they have above chance level in all three priority conditions and managed to track targets relatively well (i.e. increased tracking accuracy and precision and decreased guessing in high compared to low priority conditions). Although gaze measures reflect this unequal attention allocation (i.e. distance of eye gaze from the target decreased and proportion of time spent looking at it increased, as priority increased), Figure 8 shows that participants seem not to look at either of the targets on some trials. This is likely due to the fact that six visually identical targets were included in the display which could be easily confused with targets and participants might have accidentally tracked distractors rather than targets. It could also be a result of participants also using their covert, and not just overt, attention during tracking. This raises the question of whether the current gaze parameters measured were the appropriate ones to analyse this data (although distance looking at the targets and proportion of time spent looking at them were also measured in a similar way in past investigations; see Fehd & Seiffert, 2019; Zelinsky & Neider, 2008). Proportion of time spent on the centre of the screen and the midpoint location of the two targets were indeed considered in the analysis of gaze measures in the current experiment, but more attention should potentially have been given to the role of peripheral vision during tracking. For this reason, Experiment 3 in Chapter 3, compared unequal allocation of overt and covert attention to further explore the role of peripheral vision during MOT.

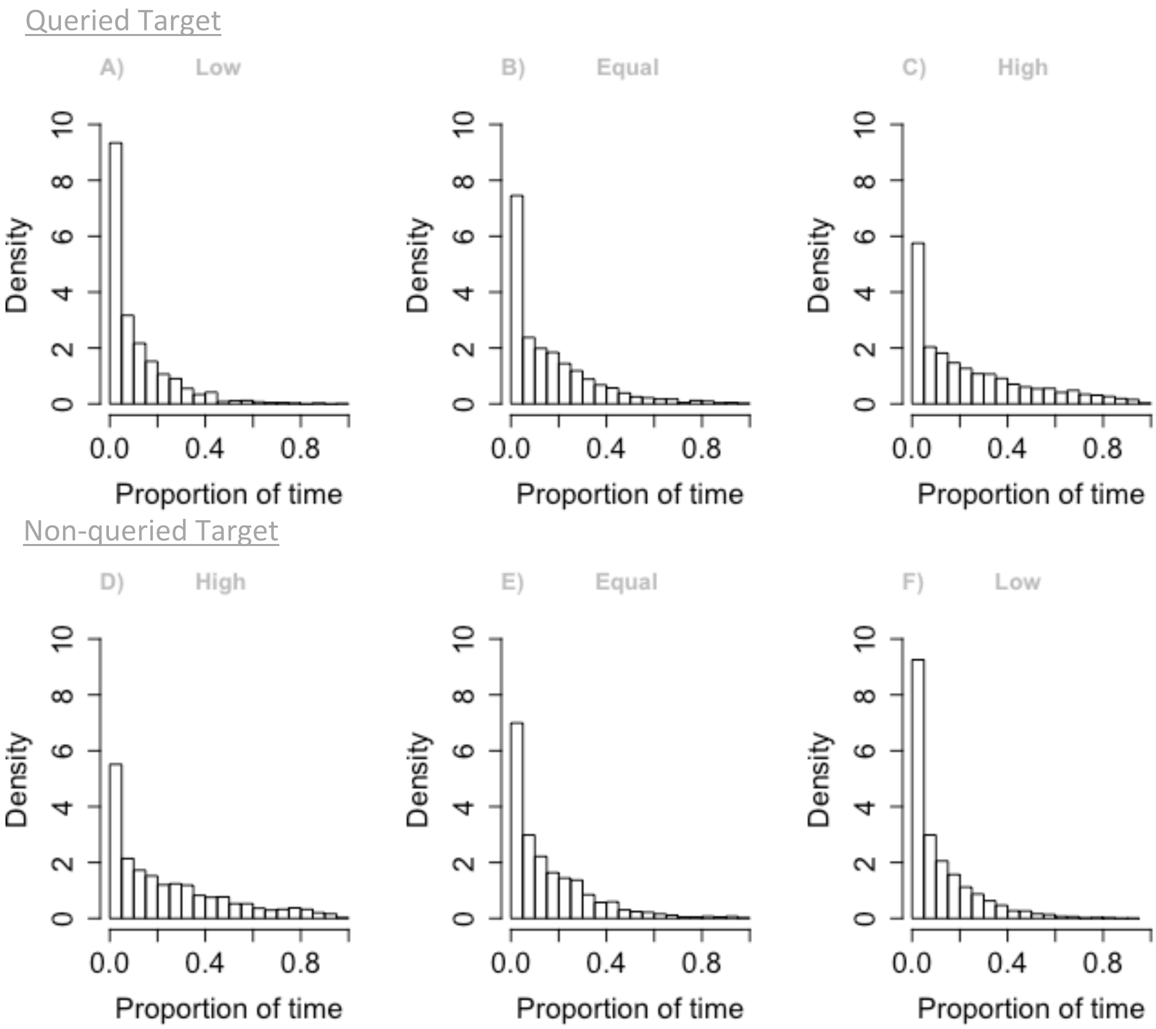


Figure 8. Panels A-C: Proportion of time spent looking at the queried target on a trial level across all participants in low (Panel A), equal (Panel B) and high (Panel C) priority conditions. Panels D-F: Proportion of time spent looking at the non-queried target on a trial level across all participants in high (Panel D), equal (Panel E) and low (Panel F) priority conditions.

2.5 Discussion

This experiment investigated participants' ability to divide their attention unevenly during a trajectory tracking MOT task while also measuring their eye movements to explore *how* attention is divided during unequal attention allocation. Priority was manipulated across three levels, low, equal and high. Participants' perceptual performance was assessed by calculating their tracking accuracy (i.e. absolute angular error) when making trajectory judgements, while gaze measures of distance from each of the targets and proportion of time spent looking at each target were also measured. Participants' perceptual performance during tracking improved as target priority increased as shown by the lower magnitude of angular error. Analysis of participants' eye movements revealed that participants' eye gaze was closer to the higher priority target while they also spent a greater proportion of time looking at the high priority target compared to the low priority target. This indicates that participants attended a target more closely when this was probed with higher probability. Figure 2 outlines several hypotheses made prior to the experiment: Participants might perform single-object tracking (Prediction A), multiple-object tracking (Prediction B) in a graded manner across priority conditions (Prediction Bi) or to the same degree of accuracy across priority conditions (Prediction Bii) or would not track individual targets at all but rely on tracking the midpoint location of the two targets (Prediction C). The findings offer support for the second scenario of prediction Bi, showing that participants perform multiple object tracking during a trial, prioritising different targets over others in a graded manner based on their associated priority. While devoting the majority of their attention to the high priority target, participants did not completely neglect the low priority target, as shown by above chance tracking performance for the low priority target, the relatively low guessing rate for even low priority targets as well as the finding that some proportion of participants' time during the trial was spent looking at the low priority target. Current evidence in favour of unequal attention allocation between high and low priority targets, is in line with past literature findings denoting that top-down instructions can guide goal-directed attention allocation (Brockhoff & Huff, 2016) and lead to graded prioritisation of some targets versus others, based on the priority associated with each one (Cohen et al.,2011; Crowe et al., 2019; Fitousi, 2016).

Our findings also offer some useful evidence regarding the structure of the attentional resource and whether this is fixed or flexible. Results from this experiment suggest that participants have some flexibility in attention allocation as they divided their attention unequally depending on the probed priorities of the targets. This is in line with aspects of flexible theories like the FLEX model (Alvarez & Franconeri, 2007) which argue that attention allocation can dynamically change during tracking such that some targets receive higher amounts of attentional resource than others. Current findings therefore provide evidence against predictions of fixed architecture theories of tracking, like the Visual Index Theory (Pylyshyn, 1989; 2001; 2007) and Multifocal Theory (Cavanagh & Alvarez, 2005; McMains & Somers, 2004; Müller et al., 2003) which claim that each target receives one fixed amount of attention (e.g. a visual FINSTs or attentional foci) irrespective of their different associated priorities and as a result would predict similar tracking performance across both targets in a given trial.

Similarly, the findings of the current study offer an insight into participants' eye movements during tracking and allow us to draw some conclusions on the eye tracking strategies they employ (Fehd & Seiffert, 2008, 2010; Zelinsky & Neider, 2008). Interestingly, in the equal priority condition, participants were found to pay a similar amount of attention to the two targets individually as well as to their midpoint location as indicated by both gaze measures (i.e. distance and proportion of time). This suggests that, when targets were probed with the same priority, participants relied on a centroid-looking strategy to some extent as well as also target-looking strategy. In the conditions where the two targets were probed with *unequal* probabilities participants were observed to primarily track the high priority target but then prioritise the tracking of the centroid location of the two targets instead of the tracking of the low priority target. This would presumably allow them to track the low priority target to some extent, but without losing track of high priority target.

These findings offer a novel insight into how the two strategies of centroid-looking and target-looking can interact and be used interchangeably during tracking of multiple objects and in particular during *unequal* attention allocation. Past studies have indicated that participants might employ a different strategy during MOT (i.e. centroid-looking versus target-looking) depending on the load of the task. In particular, evidence suggests that in low tracking loads participants are likely to employ centroid-looking strategy (i.e. when 2-3 targets are tracked) but then switch to target-looking strategy when tracking demands increase (e.g. collision with other targets, closer proximity with distractors, increased speed; Zelinsky & Neider, 2008; Zelinsky & Todor, 2010), showing evidence for clear load-dependency of the tracking strategy. In the case of the current experiment evidence suggest that the choice of using either centroid-looking or target-looking strategy might depend on other factors like priority of targets. Results show that when participants performed *unequal* attention allocation to multiple objects, the target-looking strategy was primarily used for tracking high priority targets as this allowed observers to have a high degree of precision, afforded by foveal vision. For low priority targets, a centroid-looking strategy is used more often than a target-looking strategy as this is more functional for tracking the low priority target without losing track of the high priority target. Therefore, current results show that the strategy which participants choose to use during MOT does not only depend on tracking load (Zelinsky & Neider, 2008; Zelinsky & Todor, 2010) but also on the priority of each target.

From an applied point of view, the current investigation of unequal attention allocation better reflects real-life situations in which people are required to prioritise the tracking of some targets with higher importance than others (e.g. a goal keeper having to track the movement of the player holding the ball but of other players close to him as well; a CCTV monitoring security guard in a bank having to track the movements of banks' customers more closely than the movements of bank's employees). More specifically, for example, in both sports (Abernethy et al., 2001; Ward et al., 2002) and driving (Deng et al., 2019; Kotseruba et al., 2016; Wong & Huang, 2013) settings, different objects from different locations might vary in importance therefore, it is critical for observers to allocate their attention unequally in order to make a better judgement. The current findings have important real-life implications as having established the possibility for unequal attention allocation, it would also be interesting to see to what extent this ability can be improved and trained in individuals and specifically in observers who are often required to constantly divide their attention unequally as a result of their profession (e.g. CCTV monitoring, driving) or hobbies (e.g. sports players, e-gamers).

The current experiment aimed to provide an insight as to how participants divide their eye movements (and by implication attention) to different targets when those targets have unequal priorities in an MOT task. Both perceptual performance measures and gaze measures suggest that participants prioritise tracking of the high priority target but do not completely neglect the low priority target, providing clear evidence for unequal attention allocation. Additionally, current findings provide some support for flexible architecture accounts of attention while they also show how centroid-looking and target-looking strategies are both used during unequal attention allocation.

Chapter 3 Unequal attention prioritisation of different *regions*

Work presented in this chapter was published in Attention, Perception and Psychophysics (Hadjipanayi et al., 2022). Apart from some minor edits, this chapter is presented as per the article. VH was responsible for the experiment design, programming and set-up, data collection and analysis as well as manuscript preparation. AS assisted with experiment set-up and data collection for Experiment 2, which took place in the Centre of Applied Neuroscience at the University of Cyprus. CK and CL, as primary and secondary PhD supervisors of VH, were responsible for supervising the study in all stages.

3.1 Chapter summary

In many real-life contexts, where objects are moving around, we are often required to allocate our attention unequally not only between different individual targets but sometimes between different regions of our visual field as well. Having established participants' ability to prioritise tracking of some targets versus others in Chapter 2, the aim of Chapter 3 was to explore participants' ability to unequally divide their attention between different *regions of the visual field* based on their associated levels of significance, as well as the role of eye-movements in this process. A similar trajectory tracking MOT task to Chapter 2 was used however, instead of probing individual targets with priority numbers, different tracking areas (i.e. screen regions) were probed with either a high and low or with equal priority. It is important to consider that because probed priorities were presented on the actual targets in Experiment 1 (Chapter 2), there is a possibility that this created a unique identity for those targets versus the rest of the items. This might have facilitated unequal attention allocation therefore, it is critical to investigate this process in a purer MOT task where all items are potential targets and are identical visually but also semantically. This can be done by creating different tracking areas and probing those with associated priorities (like in the case of experiments in the current Chapter), instead of probing distinct targets (like in the case of Chapter 2). Experiment 2 of the current Chapter showed that for high priority regions, accuracy (for direction of heading judgments) improved and participants had more frequent and longer fixations in that region compared with a low priority region. Experiment 3 aimed to explore the role of eye movements in unequal attention allocation and therefore, participants performed the task using either overt (i.e. foveal) or covert (i.e. peripheral) vision. Findings indicated that eye movements were functional in that they slightly improved accuracy when participants could freely move their eyes compared to when they had to centrally fixate. Additionally, replicating Experiment 2, better tracking performance was found for high compared to low priority regions, in both the free and fixed viewing conditions, but the benefit was greater for the free viewing condition. Although unequal attention allocation is possible without eye movements, eye movements seem to improve tracking ability, presumably by allowing participants to fixate more in the high priority region and get a better, foveal view of the objects. These findings can help us better understand how observers in real-life settings (e.g. CCTV monitoring, driving) can use their limited attentional capacity to allocate their attention unequally in a demand-based manner across different tracking regions.

3.2 Introduction

3.2.1 Overt versus Covert attentional tracking

The role of eye movements during attention allocation has been investigated by looking at different eye-movements strategies participants employ (e.g. centroid-looking vs target-looking; Fehd & Seiffert, 2008; 2010; Zelensky & Neider, 2008). These tracking strategies indicate the different roles of overt (i.e. foveal) vs covert (i.e. peripheral) vision during attentional tracking. In particular, Landry et al., (2001) investigated the eye movements of participants when they monitored objects for potential collisions during a simulated air-traffic control tracking task. Results indicated increased saccades when participants monitored targets on a potential collision course compared to when they monitored other targets that were not likely to collide. This evidence indicates that observers tend to fixate on items, particularly when tracking gets difficult. This suggests that making eye movements to targets facilitates tracking performance as saccades can allow for a foveal view of objects, which can in turn aid in updating their exact location. In this context, Zelinsky and Todor (2010) investigated the role of 'rescue saccades' in MOT, which refer to saccades initiated when tracking load increases (e.g., when the target is close to a distractor), highlighting the importance of overt attention and the oculomotor system in events that might cause temporary loss of tracking (e.g., during occlusion).

However, the importance of *covert* attention and peripheral vision during attentional tracking has also been established, suggesting that what we fixate is not necessarily what we attend to. In particular, it has been found that task-relevant stimuli can be detected and processed when they appear both inside and outside the fixation region (Lichtenstein-Vidne et al., 2007; Linnell & Humphreys, 2004). However, evidence suggests that observers tend to rely on peripheral vision at lower tracking loads and switch to foveal vision when tracking demands increase (Zelinsky & Neider, 2008).

Vater et al. (2016) investigated whether peripheral vision can be used to track multiple moving objects and detect single-target changes. Their results indicated that peripheral vision is naturally used to detect changes in motion and form. Taking it further, Vater et al. (2017b) reported that detection of changes in form and motion is faster when changes occur close to the fixation region. If the location of fixation is further away from the location of target change, motion changes are still detected with the same accuracy while form changes are less accurately detected. This suggests that peripheral vision is more sensitive to changes in motion than in form. The use of peripheral vision for target motion and form detection has also been replicated in sports settings using simulated environments (Vater, 2019; Vater et al., 2017a). Taken together, these studies provide evidence for the plausibility of using peripheral vision to track multiple moving targets and to detect motion and form changes in MOT tasks. However, the role of overt and covert attentional tracking has primarily been investigated in MOT settings where all targets have an *equal* level of importance. To my knowledge, no study has investigated the role of peripheral vision in MOT contexts where different targets have different levels of importance therefore attention needs to be allocated in an *unequal* manner. Such an investigation can shed light on potential eye movement strategies participants employ when they have to divide their attention unevenly across different regions of their visual filed.

3.2.2 Unequal attention allocation on different regions of the visual field

Past findings (Cohen et al., 2011; Crowe et al., 2019; see also Chapter 1 of this thesis) investigated unequal attention allocation to different *individual* targets. However, little attention has generally been given in the MOT literature, to unequal attention allocation between *entire regions* of the visual field and the role of eye movements in this process. In many real-life contexts observers are often required to split their attention across different regions of the visual field which have different levels of importance. For example, a driver is required to split attention unequally between areas of higher importance like the road their car is moving into, and areas of less, yet not completely negligible, importance like pavements. Although a lot of work has been done on investigating observer's attention allocation across different areas of the visual field (Carrasco, 2018; Carrasco & Barbot, 2019; Chu et al., 2021; Kramer & Hahn, 1995; Zhu et al., 2019) to my knowledge, goal-directed *unequal* attention allocation to different regions and in particular the role of eye movements in this process, have largely been understudied in MOT literature.

3.2.3 Aims of the Chapter 3

The experiments reported in this chapter aimed to investigate whether participants can allocate their attention unevenly across two regions of the visual field as well as the role of eye movements in this process. A modified trajectory-tracking MOT task was used where two distinct tracking regions were probed with high and low priority or equal priority. In the trajectory-tracking MOT task used in Chapter 2, probed priorities were presented on the actual targets, creating an element of Multiple Identity Tracking (MIT) as well, as participants were required to assign a certain priority (which could be used as an identifier, e.g. 'the high one') to each target. This could have created identity-location bindings, which refer to perceptual associations created between a targets' unique identity and its location (Howe & Ferguson, 2015; Oksama & Hyönä, 2008; Saiki, 2002). Identity encoding is a process that requires additional attentional resource and could have influenced attention allocation of participants (Cohen et al., 2011). Therefore, in order to make more conclusive judgements regarding participants' ability for unequal attention allocation, it was important to explore this in a purer MOT task, in which individual targets are not assigned a unique identity. This was addressed in the current Chapter, using a modified MOT task, where different tracking regions, and not individual targets, were associated with a certain probability of getting questioned. This chapter explored participants ability to prioritise tracking of targets in some *regions* of the screen versus others, in an unequal and graded manners based on the priorities associated with each region.

The aim of Experiment 2, was to investigate whether attention can be allocated unequally across two regions of the visual field, by examining differences in accuracy with which participants report the direction of heading of an item probed in a low, equal, or high priority region. In Experiment 3 the functional role of eye movements in unequal attention allocation was explored. Although the usefulness of peripheral vision for detecting target changes during MOT tasks has already been established (Vater et al., 2016; 2017a; 2017b), the role of covert attention has not been investigated when attention is unequally allocated. Participants' performance in free-viewing and fixed-viewing conditions was compared to investigate a) whether attention can be unequally allocated by relying solely on peripheral vision (i.e. fixed-viewing condition) and b) which, if any, of the two viewing conditions, free (i.e. foveal tracking of objects) or fixed (i.e. peripheral tracking of objects), facilitates trajectory tracking in the current modified MOT task.

3.3 Experiment 2

The aim of Experiment 2 was to investigate whether participants were able to unequally allocate their attention to different regions in a graded manner based on the priority associated with each regions. Another goal was to explore whether the effect of goal-directed unequal attention allocation observed in Crowe et al. (2019) and in Chapter 2 can also be observed in an experimental paradigm where the possibility of forming identity-location bindings is removed.

3.3.1 Method

Openness of data: The aims and hypotheses of Experiment 2 were preregistered on the Open Science Framework and can be found at: https://osf.io/wkcj5/, together with the data and analysis scripts. Ethical approval was obtained from the National Bioethics Committee of Cyprus (ΕΕΒΚ/ΕΠ/2020/26). The study was conducted according to the revised Declaration of Helsinki (2013).

Participants. 33 individuals (18 females), with age (M ± SD), 22.7 ± 2.9 years, were recruited from the University of Cyprus and surrounding areas, via the Experimental Credit Scheme and word of mouth. Testing of participants was carried out at the Centre of Applied Neuroscience (CAN), University of Cyprus. To be consistent with Chapter 2, a sample size of 33 participants was chosen. Based on the power calculation described in Chapter 2, a sample of 33 participants gives us at least 99% power of detecting a similar effect at an alpha of.05. Participants were required to have normal or corrected-normal vision and be less than 35 years old.

Design. The priority of screen regions (upper half and lower) was manipulated in a within-subjects design with three levels: high (70%), equal (50%), and low (30%). On a given trial, the combined values total 100 so numbers were represented in three different combinations: 70-30 (i.e. 70 in the upper and 30 in the lower region of the screen), 50-50 or 30-70 (i.e. 30 in the upper and 70 in the lower region of the screen). These numbers represent the likelihood of the 'queried' item appearing in the upper or in the lower region of the screen respectively. Three dependent variables were measured: tracking error, gaze time spent on each screen region, and gaze deviation from the centre. Tracking error was measured in the same way like in Chapter 2. Proportion of gaze time spent looking at each screen region was computed on the basis of all the gaze samples, excluding blinks. Note that as a result, gaze time includes fixations, saccades, and epochs of smooth pursuit. Gaze deviation from the centre was indexed as the vertical distance above or below the centre of the screen.

Materials. The same apparatus as in Chapter 2 was used, apart from the following changes in the monitor and eye tracking equipment. Stimuli were presented on a PC running Windows 7. A 24" BenQ monitor was used, with a resolution of 1,920 x 1,080 pixels, running at 60 Hz. The stimulus window was 1,200 x 900 pixels. At a viewing distance of 70 cm, 1˚ corresponded to 45 pixels. An Eyelink 1000+ (SR Research Ltd.) video-based tracker was used. The eyes were tracked at a sampling rate of 1,000 Hz. The eye tracker was calibrated at the start of every block of trials (using the in-built 9-point calibration routine). Saccades and fixations were parsed offline using the velocity and acceleration criteria of $30^{\circ}s^{-1}$ and $8000^{\circ}s^{-2}$, respectively.

Details on the actual trajectory-tracking MOT task and characteristics of stimuli (e.g. size, colour, speed etc) were again the same as Chapter 2, apart from the following differences. Since the aim of this chapter was to explore participants' ability to perform unequal attention allocation across different regions of the visual field, priority numbers were not presented on the actual targets like in the case of Chapter 2. In the current modified MOT task, two distinct tracking areas were formed (i.e. left and right) by dividing the screen horizontally. Priority numbers were presented on screen regions and they represented the likelihood that participants would be asked to report direction of any target from that region.

Procedure. Figure 9 illustrates the timeline of a trial. A fixation screen appeared at the beginning of each trial and the experimenter initiated the trial upon accurate fixation. The fixation point was a vertical line of 0.4˚ of visual angle at the centre of the middle line dividing upper and lower screen regions. The inter-trial interval was minimum 1 seconds but often longer as it was dependent on the participant fixating accurately and the experimenter initiating the trial manually. Recording terminated at the end of every block of 30 trials.

Throughout the experiment, the screen was divided horizontally in two regions of equal area. At the beginning of each trial, before the discs appeared, the two likelihoods were presented on the screen for 3 seconds, one in the upper and one in the lower region of the screen. For instance, in trials with the combination of 70 in the upper and 30 in the lower region of the screen, the 'queried' item that participants had to respond to, came from the upper region with a probability of 0.7 and from the lower region with a probability of 0.3. Participants were given clear instructions on what these numbers meant before starting the practice trial and had the opportunity to ask any questions.

Participants were instructed to keep tracking the discs while they were moving. When the trial ended, only one disc remained on the screen. The queried item would either be in the upper or in the lower region of the screen depending on the probed priority level assigned to each region. The participants' task was to click, using the left mouse button, on the direction they thought this disc was moving. Participants first clicked inside the disc to 'activate' a "dial" on the disc with an arm of 1.14˚ extending from the item's centre. The initial direction of the arm was set randomly. Participants then used the mouse to move the arm to indicate the estimated direction of travel and confirmed their answer with a second left mouse click. Feedback, consisting of a green arrow, of size 1.14˚ of visual angle, was given on each trial, indicating the correct direction of travel.

Participants performed 10 practice trials and then 150 experimental trials equally divided into 5 blocks of 30 trials. Within a block of 30 trials, there were ten trials of each of the following types: 70-30; 30-70; 50-50 (upper – lower screen region). The frequencies of being probed in the upper or lower region of the screen followed the nominal probabilities, i.e., 7-3; 3-7 and 5-5. Therefore, within a block there were 14 trials in which a target from the high priority region was probed, 10 trials in which a target from the equal priority region was probed and 6 trials in which a target from the low priority region was probed. The order of trials was randomised for each participant. Hemifield presentation was counterbalanced across trials for every participant such that, the upper and lower screen regions were probed an equal number of times. The eye tracker was recalibrated before each block. The total testing time was approximately 60 minutes.

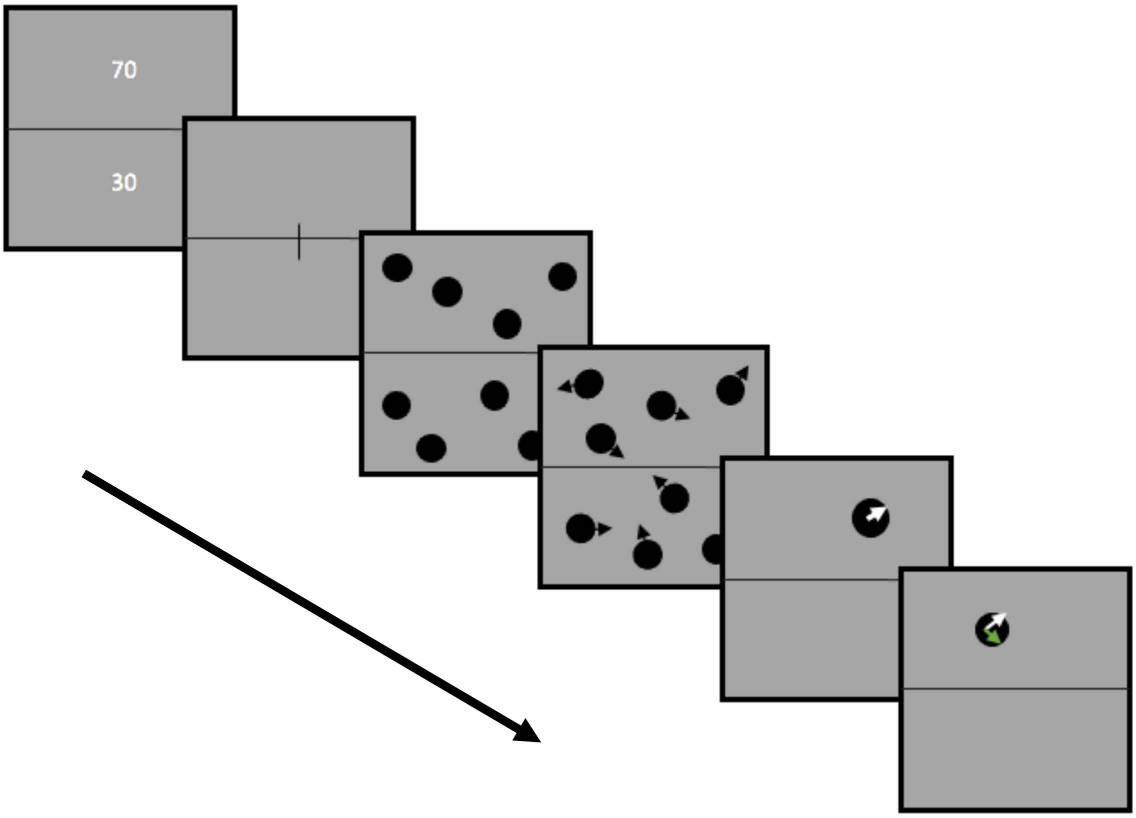


Figure 9. Trajectory tracking task timeline. At the beginning of the trial, priority numbers appeared in the upper or in the lower region of the screen respectively for 3 seconds. These numbers were either 70-30, 30-70 or 50-50. Then numbers disappeared and fixation line was presented. Subsequently, eight discs appeared on the screen, four in the upper and four in the lower regions of the screen. Then discs started moving around the screen without crossing the horizontal boundary (the black arrows were not presented on the screen, but are used here to represent movement) for a period of 6 – 8 seconds. After the period of movement all discs disappeared, except one (which was either in the upper or in the lower screen region based on the probe probability of each region). Participants were then asked to click on the direction they thought the disc was going. After participants’ response, feedback was presented on the screen. A green arrow appeared indicating the target's correct trajectory.

3.3.2 Results and Discussion

Data was analysed using Linear Mixed Effects models (LMEs; Baayen, Davidson & Bates, 2008; Barr et al., 2013) with the lme4 package (Bates et al., 2015) for the R computing environment (R Core Team, 2015). Linear Mixed Effects analysis was conducted with priority of screen regions entered as a fixed effect and a random intercept for subjects. Data for both perceptual performance and gaze measures were analysed aggregated across trials to ensure that the observations were normally distributed. P-values are reported which derived from a likelihood ratio test comparing the full model, including the predictor variable of priority, to the null model which included a random intercept for subjects only, without priority included.

Perceptual performance. Figure 10 indicates tracking performance of participants in all three priority conditions. If people responded completely randomly, we would expect an average absolute tracking error of 90°. Clearly, the majority of participants performed better than that. Moreover, tracking accuracy improved as priority increased. Specifically, there was a main effect of screen priority on magnitude of angular error, $\chi^2(1) = 29.65$, $p < .001$, whereby as the priority of screen region increased, the magnitude of angular error decreased, (b = -0.421, SE = 0.06, t = 6.12, p <.001).

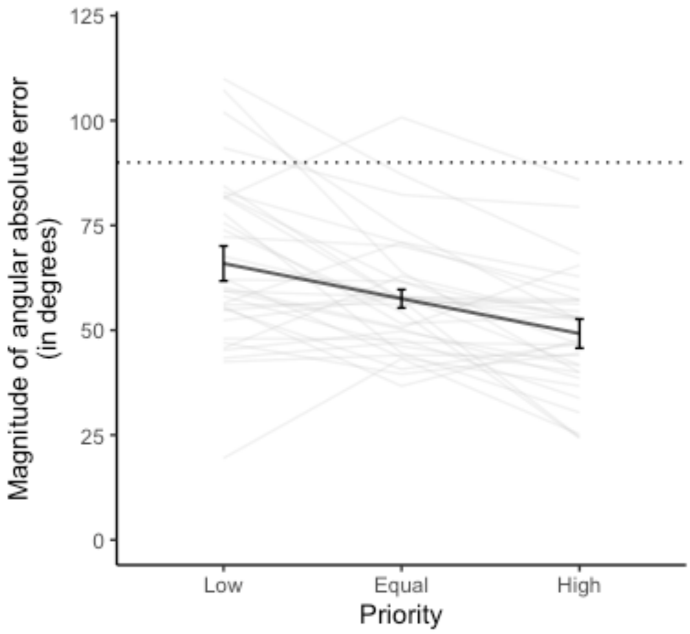


Figure 10. Magnitude of angular absolute error for each priority level. Black bold line indicates average magnitude of angular error across all 33 participants. Error bars indicate 95% confidence intervals based on Morey (2008). Grey lines indicate magnitude of angular error for each participant individually. Dashed line indicates the level of chance performance.

Next, similar to Chapter 2 of this thesis, a model based analysis was conducted to estimate proportion of guessing and precision of participants during tracking. The same method as in Chapter 2 was used. Figure 11 illustrates the mixture model fits for error data pooled over all participants, at each of the three priority levels. The parameter P_G represents the probability of a random guess and the parameter κ represents tracking precision (the concentration of the von Mises component). The higher the κ value, the narrower the distribution around the mean, illustrating higher precision. The model fit is consistent with the analysis of error data above, illustrating that with increasing priority, the proportion of guessing decreases and precision increases, replicating the results of Chapter 2. [3] However, it could also be argued that precision per se did not vary as such between the equal and high priority conditions but was just a result of a target being probed in the region that participants were not concentrating on.

[3] Similar to Chapter 2, when model analysis was done on individual participants, the effects of priority on the parameters of proportion of guessing and tracking precision were more fragile, presumably because more data would be needed to estimate the model parameters reliably for each participant individually.

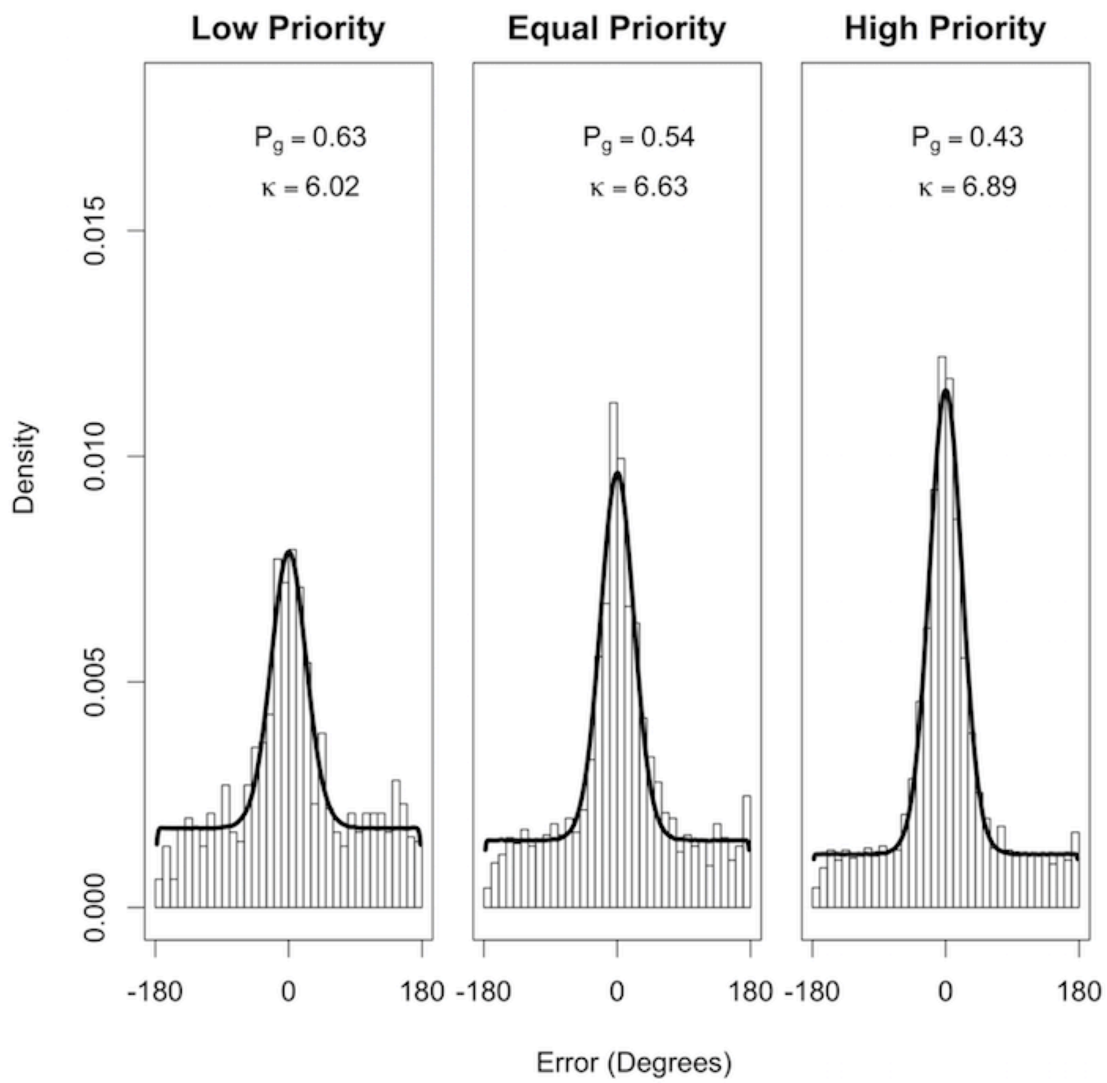


Figure 11. Fits of mixture model for the data pooled across participants at the three priority levels. The density plot demonstrates the experiment data and the black density line illustrates the model fit. The best-fit parameters of the proportion of guessing (PG) and precision of tracking (κ) are also shown.

Gaze measures. Two measures were drawn from the eye tracking data: proportion of time spent by each participant looking at the upper screen region and the mean vertical distance (in degrees) from the centre of the screen, in each of the three different priority conditions (low, equal or high). These two measures were used to assess how participants allocate their overt attention during tracking across the two regions of the screen. It is worth noting that mean vertical distance from the centre is not a measure of how much participants *moved* their eyes during tracking, but rather a supplementary gaze measure for how overt attention was allocated across the two screen regions. The proportion of time and mean vertical distance, averaged across trials, were entered into the LME analysis in the same way as the magnitude of angular error.

Figure 12 indicates that the higher the priority a screen region was probed with, the more time was spent looking at that region. There was a significant effect of priority on proportion of time spent looking at upper screen region, χ^2 (1) = 69.09, $p < .001$. Participants spent more time looking at the upper region when it was more likely to be probed, (b = 0.011, SE = 0.001, t = 10.77, $p < .001$). Since Figure 12 illustrates proportion of time spent looking at the upper screen region, it offers a reflection of the proportion of time spent looking at the lower region as well (i.e., proportion of time spent looking at lower region when probed with high priority is equal to 1 minus the proportion of time spent looking at upper region when probed with lower priority). Figure 12 indicates two potential strategies which might have been used during tracking. Although the majority of the participants allocated their attention in accordance to the priority of targets (i.e. allocated more attention to a target as priority increased) it is also worth noting that some participants looked at the same region irrespective of the priority instructions something which is expected and attributed to individual differences in tracking behaviour and preferred strategies employed.

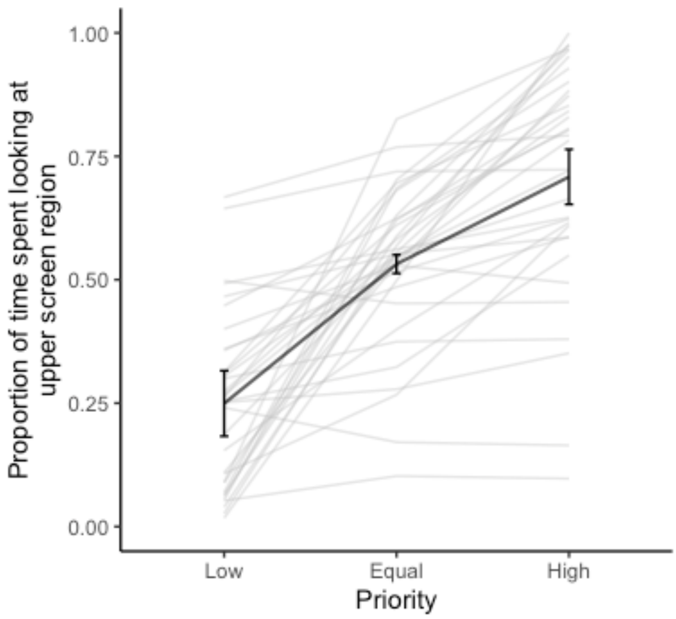


Figure 12. Proportion of time spent at the upper screen region, for each priority level presented. Black bold line indicates average proportion of time spent looking at the upper screen region across all 33 participants. Error bars indicate 95% confidence intervals based on Morey (2008). Grey lines indicate proportion of time spent looking at the upper screen region for each participant.

The finding that participants spent more time looking at a screen region that was probed with higher priority (Figure 12), is further supported by the analysis of the mean vertical distance of eye gaze from the centre. Participants fixated, on average, higher up the screen when the upper region was probed with a higher priority and further down the screen when the upper region was probed with a lower priority. There was a significant effect of priority of the upper screen region on mean vertical distance from the centre, $\chi 2$ (1) = 77.32, $p < .001$, with distance increasing as the upper screen region was more likely to be probed (b = 0.099, SE = 0.009, t = 10.82, p <.001). These findings provide further evidence for participants' gaze behaviour being influenced by priority, suggesting that they were looking more at high versus low priority regions.

Exploratory analysis

An outstanding question is whether and to what extent the gaze bias influenced perceptual performance. Therefore, the relationship between the proportion of gaze time spent in the probed region and absolute tracking error was assessed. The correlation for each individual participant was computed at a trial level, pooled over the three conditions. Figure 13 shows the distribution of these correlations and demonstrates that 76% of the individual correlations are negative. The mean correlation across participants of -.14 was significantly different from 0, $t(32) = -4.22$, $p < .001$. This result indicates that the more the participants were looking on the probed screen region, the lower their absolute tracking error, with the t-statistic again highlighting that this is a relatively robust effect, similar to Chapter 2. However, similar to the discussion made on findings of Experiment 1, taking into account the 'cued-factor' and the idea that most or even all of the measured variables in a dataset have non-zero correlations (Tibshirani, 2014), relevance and inferences from these tests need to be interpreted with caution.

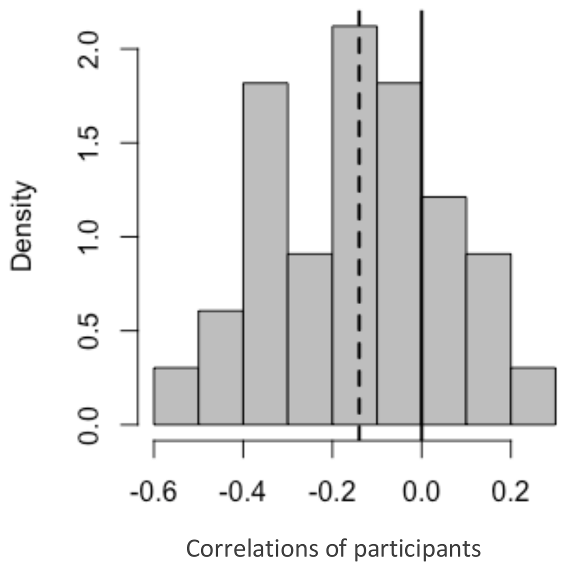


Figure 13. Histogram of correlations of individual participants between the proportion of time spent looking at the probed region and the tracking error (in degrees). The vertical bold line indicates 0 correlation and the vertical dotted line indicates the mean of all individual correlations.

The perceptual performance and gaze data of Experiment 2 suggest that attention was allocated unequally between the two visual fields in a top-down fashion, with attention preferentially directed to high versus low priority regions of the screen, as evidenced by improved tracking performance (Figure 10), prolonged eye gaze (Figure 12), and greater distance from the horizontal midline. Participants seemed to allocate their attention and focus on high priority regions of the screen during movement of objects, resulting in decreased angular error, decreased guessing rate, and increased precision of estimating the discs' trajectory. This finding is a form of probability matching (Eriksen & Yeh, 1985) and supports the idea that participants devoted the majority of their attention to the high priority region, but did not completely neglect the low priority regions. Current results replicate and extend those of Crowe et al. (2019) providing support that in a MOT task in which the objects are not individuated, participants are able to allocate their attention unequally between different tracking regions depending on the priority assigned to each region.

In this experiment eye movements were used as a direct measure of attention allocation. However, there may not be a one-to-one mapping between the loci of attention and gaze. A dissociation for both reflexive (Hunt, & Kingstone, 2003a) and voluntary (Hunt & Kingstone, 2003b) shifts between overt and covert attention is well established, supporting the possibility of shifting attention without shifting eye gaze (Kerr, 1971; Posner, 1980). However, *just prior to generating a saccade*, attention is focused on the future saccade target (Hoffman & Subramaniam, 1995; Juan et al., 2004; Kowler et al., 1995; Murthy et al., 2001; Sato & Schall, 2003; Schall, 2004). Only in that brief timeframe there appears to be an obligatory coupling between overt and covert attention. Participants in a MOT task can still attend to a target or specific region of the visual field using their peripheral vision, without moving their eyes (Vater et al., 2016; 2017a; 2017b). Therefore, the extent to which foveal tracking (through eye movements) or peripheral tracking (through off-target gaze fixation and peripheral vision) facilitates performance in the current task, is yet to be determined. The findings of Experiment 2 suggest an association between time spent looking at a screen region and tracking accuracy (Figure 13). Experiment 3 aimed to extend this finding and assess the causal role of eye movements in the current trajectory tracking MOT task. Tracking performance of participants who freely moved their eyes during tracking (free-viewing), was compared with performance of those who kept their gaze fixed at the centre (fixed-viewing).

3.4 Experiment 3

This experiment aimed to investigate whether foveal or peripheral tracking of objects facilitates tracking performance in the current MOT task, as well as whether unequal attention allocation is possible with exclusive reliance on peripheral vision and covert attention. The critical role of peripheral vision has been identified in MOT tasks where equal attention allocation was required (Sears & Pylyshyn, 2000; Vater et al., 2016, 2017a, 2017b). However, to my knowledge no study has explored peripheral tracking in a MOT task where unequal allocation of covert attention between screen regions is beneficial. In this study, priority was manipulated within subjects in the same way as in Experiment 2. The screen was divided vertically instead of horizontally to investigate whether the priority effects seen in Experiment 2 generalise to a different lay-out. Viewing condition was manipulated between subjects. Participants in the free-viewing condition were instructed that they were free to move their eyes around the screen during tracking, while participants in the fixed-viewing condition were instructed to keep their eyes fixated at the centre of the screen throughout the trial and track moving objects with their peripheral vision.

3.4.1 Method

Openness of data: The aims and hypotheses of Experiment 3 were preregistered on the Open Science Framework and can be found at: https://osf.io/bfje4/, together with the data and analysis scripts. Ethics approval was obtained from the School of Psychological Science Research Ethics Committee at the University of Bristol (113064). The study was conducted according to the revised Declaration of Helsinki (2013).

Participants. 66 individuals (48 female) with age (M ± SD), 20.2 ± 2.7 years, were recruited from the University of Bristol, via the School of Psychological Science Experimental Hours Scheme, in return for course credit, and adverts on the School's webpage, in return for the two highest achievers receiving a £50 Amazon voucher each. A top performer was identified from each viewing condition based on a performance score calculation (see below). Testing took place at the labs of the School of Psychological Science at the University of Bristol. For purposes of consistency with Experiment 2, a sample size of 66 participants was chosen (i.e. 33 participants in each of the two viewing conditions). Based on the power calculation described in Chapter 2, a sample of 33 participants gives us at least 99% power of detecting a similar effect at an alpha of.05. Participants were required to have normal or corrected-normal vision and be less than 35 years old.

Design. This study involved a mixed design. Priority was manipulated as a within-subjects factor with three levels (Low:30, Equal:50, and High:70) in the same way as in Experiment 2. Viewing-condition was manipulated as a between-subjects factor with two levels (free viewing versus fixed viewing). The same dependent variables as in Experiment 2 were used.

Materials. The same apparatus as in Chapter 2 was used regarding the monitor and eye tracking equipment used. Details on the actual trajectory-tracking MOT task and characteristics of stimuli (e.g. size, colour, speed etc) were the same as in Experiment 2, apart from the following differences. In the current experiment the screen was divided vertically (instead of horizontally like in Experiment 2) in order to investigate whether the priority effect observed in Experiment 2 is replicated with a vertical screen division as well.

Procedure. The procedure regarding the number of practice and experimental trials, number of blocks and testing duration was identical to that of Experiment 2. In the fixed-viewing condition, participants were instructed to keep their eyes fixated at the centre of the screen throughout the tracking period. Compliance of participants with these instructions was encouraged by close monitoring of their eye movements by the experimenter, and regular reminders to keep fixating in the centre of the screen. At the end of every block, participants were provided with a score which reflected their performance on that particular block. This number represented the percentage of trials in which they specified a direction of movement which was within 20˚ of the correct direction of the item. This was done for purposes of participants' compensation, to determine the two highest achievers (i.e. participants with the highest score) who would receive £50 each.

3.4.2 Results and Discussion

As in Experiment 2, LME analyses for the key perceptual and gaze measures was used. Priority (within-subjects continuous factor) and viewing condition (between-subjects categorical factor) were entered as fixed effects in the full model, along with their interaction. Both the null model and the full model allowed for a random intercept for subjects. For both perceptual performance and gaze measures, the full model (including the predictor variables of priority and viewing condition, and their interaction) was compared to the null model which included a random intercept for subjects only. The effects of priority, viewing condition, and their interaction are reported for every dependent variable from the full model, given that it was found to better predict the data compared to the null model. Data for both perceptual performance and gaze measures was analysed aggregated across trials, to ensure normality of observations.

Perceptual Performance. Figure 14 indicates again better-than-chance tracking performance of participants in both free-viewing (Panel A) and fixed-viewing conditions (Panel B) across all three priority levels, suggesting that the task could be completed even when participants were not allowed to move their eyes. In both viewing conditions, there was better tracking accuracy in high versus low priority conditions. However, in the free-viewing condition, accuracy increased in a linear manner with priority. In contrast, in the fixed-viewing condition, there was similar tracking accuracy between equal and high priority conditions. The full mixed effects model (i.e. priority and condition as fixed effects along with their interaction) fit the data significantly better than the null model, $\chi2$ (3) = 46.7, $p < .001$. Specifically, priority had a significant effect on the magnitude of angular error, ($b = -0.416$, $SE = 0.06$, $t = -6.82$, $p < .001$). In both viewing conditions, as priority increased, the magnitude of angular error decreased. The viewing condition did not have a significant effect on the magnitude of angular error, ($b = -9.422$, $SE = 5.38$, $t = -1.75$, p = .082). However, there was a significant interaction between priority and viewing condition ($b = 0.234$, $SE = 0.086$, $t = 2.72$, p = .007), suggesting that priority influenced magnitude of angular error differently across the two conditions, with participants demonstrating lower error in free-viewing (M=47.12, SD=49.61) compared to fixed-viewing (M=54.90, SD=53.66) conditions in the high priority screen regions (Figure 14).

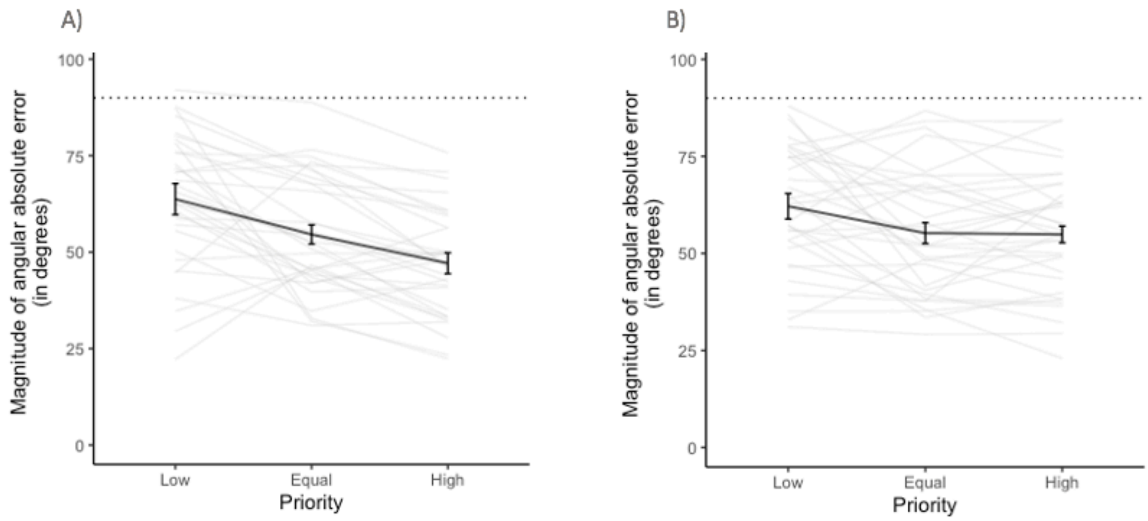


Figure 14. Magnitude of angular absolute error for each priority level in both free-viewing (Panel A) and fixed-viewing (Panel B) conditions. Black lines indicate average magnitude of angular error across all 33 participants in each viewing condition. Error bars indicate 95% confidence intervals based on Morey (2008). Grey lines indicate magnitude of angular error for each participant individually. Dashed horizontal lines indicate level of chance performance.

Figure 15 shows the mixture model fits for the three different priority conditions in free-viewing (Panel A) and fixed-viewing (Panel B) conditions of Experiment 3. In line with initial predictions and the results of Experiment 2, model fits for the free-viewing condition are consistent with the analysis of error data for that condition (Figure 15, Panel A): with increasing priority, tracking accuracy increased, the proportion of guessing decreased and precision increased.[4] For the fixed-viewing condition, the model continues to capture the data

[4] Similar to Experiment 1 (Chapter 2) and Experiment 2 (Chapter 3), when model analysis was done on individual participants, the effects of priority on the parameters of proportion of guessing and tracking

well. However, no clear decreasing pattern of guessing is observed across the three priority conditions with similar guess rates in the equal priority condition and high priority condition. This is expected, given the similar accuracy levels of participants observed in these two priority conditions (Figure 15, Panel B). Precision increased as priority increased. Although the model has generally a good fit on the majority of data, it is worth noting however that a lack of fit can be observed in the low priority condition of the fixed-viewing condition. In particular, the number of answers with almost 0 angular error in direction of heading judgements is much higher that the fit suggests. This is likely to be a result of the model being unable to capture such a narrow pick of responses with almost 0 error.

precision were more fragile, presumably because more data would be needed to estimate the model parameters reliably for each participant individually.

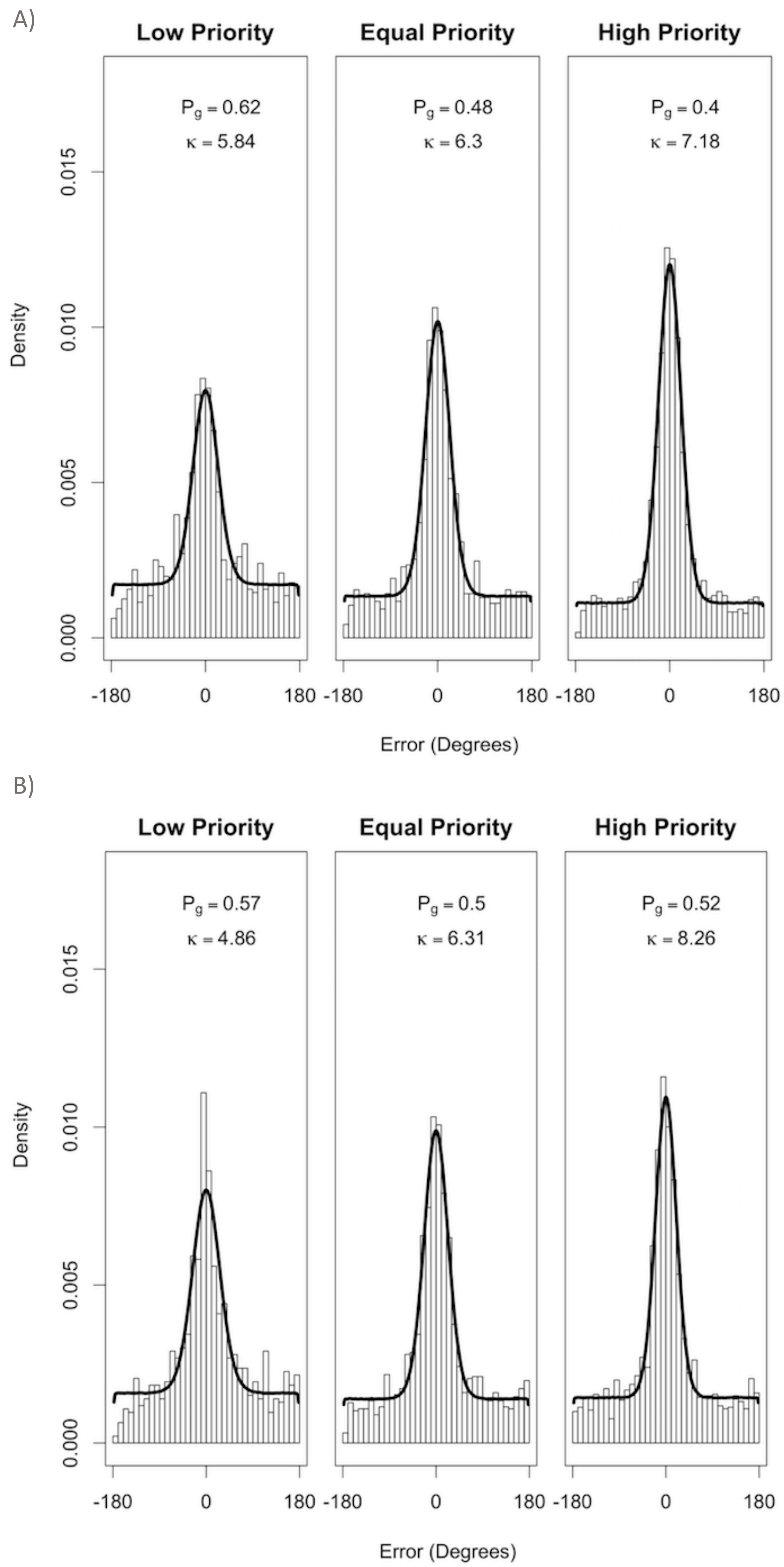


Figure 15. Fits of mixture model for the three different priority conditions in free-viewing (Panel A) and fixed-viewing (Panel B) conditions of Experiment 3. The density plot demonstrates the experiment data and the black density line illustrates the model fit. The

best-fit parameters of the proportion of guessing (PG) and precision of tracking (κ) are also shown.

Gaze measures. Two measures were drawn from eye tracking data: proportion of time spent looking at the left screen region and the mean horizontal distance (in degrees) from the centre of the screen, at each of the three different priority levels (i.e. low, equal, or high). These measures were averaged across trials for each participant and analysed with LME models in the same way as the angular error. First, however, the efficacy of the viewing condition manipulation was assessed to ensure that the participants' eye movements matched the instructions they were given. Figure 16 indicates the average distance of eye gaze from the centre of the screen for each participant across the two viewing conditions. This was achieved by measuring the distance of each eye gaze sample from the centre of the screen, then calculating the average of those for each trial, and then across trials for each participant. It is worth noting that there is an overlap between the fixed viewing condition and the free viewing condition. This is attributed to two reasons: 1) We do not expect participants in the fixed-viewing condition to have an average distance of 0. Even if they complied with the instructions perfectly and never let their gaze move away from the centre by more than, say, a degree, we would expect small movements around fixation (micro-saccades and drift; Martinez-Conde et al., 2013; Rolfs, 2009); 2) It is possible that some participants in the free-viewing condition followed a fixed-viewing strategy and looked at the centre of the screen which they possibly found more effective or comfortable for tracking (which further highlights the importance of investigating overt and covert unequal attention allocation). It is worth noting that while there is some degree of overlap in the two distributions, it is clear that the majority of participants in the free-viewing condition moved their eyes around much more than participants in the fixed-viewing condition. Participants in the fixed-viewing condition also had much smaller variance in their distance travelled, as would be expected if they largely complied with the instruction to keep their gaze fixed.

With micro-saccades having an average magnitude of 1 degree (Martinez-Conde et al., 2013) and also considering the fact that small movements around the fixation point were inevitable especially given the nature of the set-up and task itself, an exclusion criterion of 2 degrees average distance from the centre was set for participants in the fixed-viewing condition to ensure that no participants included in the analysis had excessive and unreasonable eye movements in this condition. No participant exceeded that average from the fixed-viewing condition so no participant was excluded from the analysis.

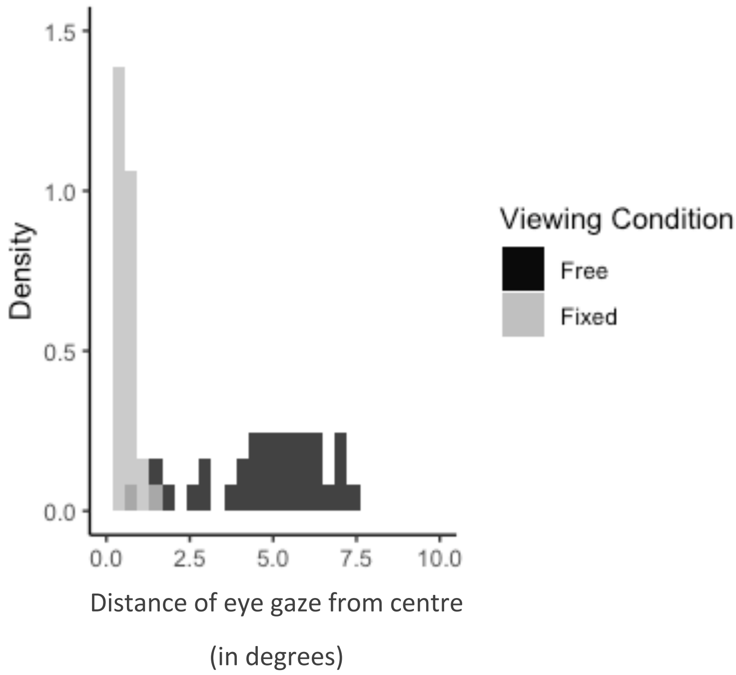


Figure 16. Average distance of each participant’s eye gaze from the centre in the two viewing conditions.

Figure 17 indicates the average proportion of time spent looking at the left screen region, as a function of priority of that area, across both viewing conditions. For the free-viewing condition, with increasing priority of the left region of the screen, participants spent more time in that region. However, in the fixed-viewing condition, roughly the same proportion of time was spent looking at the left screen region across all priority levels. To some extent, this result simply suggests that participants in the fixed-viewing condition complied with the instructions to fixate centrally. Nevertheless, we might have expected them to have subtle biases close to fixation, for example, through their microsaccades (Engbert & Kliegl, 2003). Such a bias would have shown up in this metric, because samples were simply tallied to the left and right of the vertical midline. Indeed, there *is* an overall bias toward fixating on the right side of the vertical midline, but this bias does not seem to be affected by priority.

The full LME model with priority and condition as fixed effects along with their interaction, fit the data significantly better than the null model, $\chi2$ (3) = 117.64, $p < .001$. Specifically, there was a significant effect of priority on proportion of time spent looking at the left screen region (b = 0.01, SE = 0.001, t = 13.32, $p < .001$). Also, there was a significant effect of viewing condition on proportion of time spent looking at the left screen region (b = 0.41, SE = 0.006, t = 6.68, p <.001). A greater proportion of time was spent looking at the left screen region in free-viewing (M= 0.48, SD=0.24) compared to fixed-viewing condition (M=0.42, SD=0.14). Furthermore, there was a significant interaction between priority and viewing condition (b = -0.009, SE = 0.001, t = -8.47, $p < .001$).

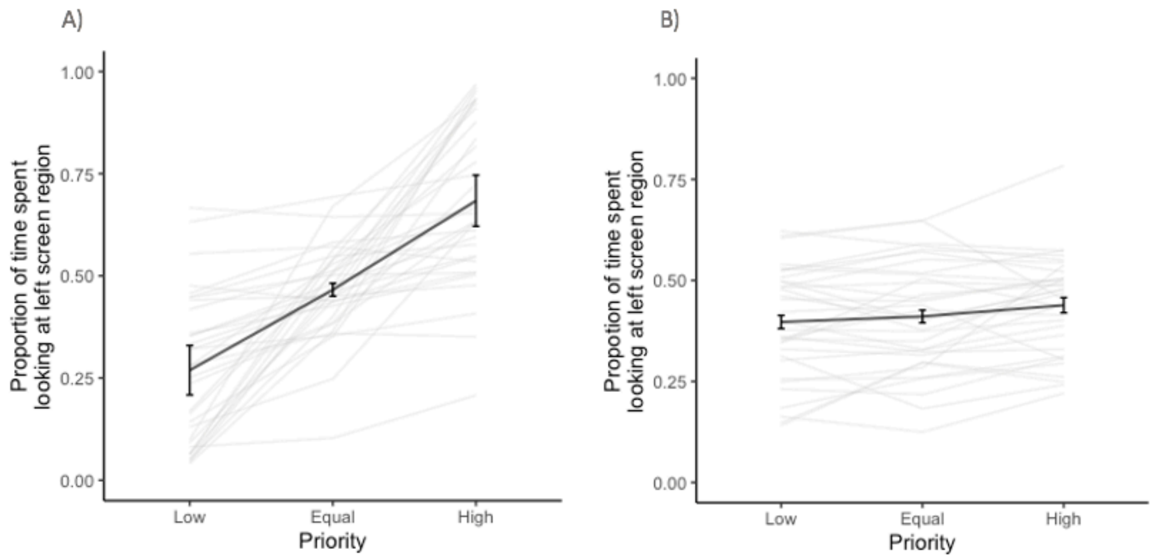


Figure 17. Proportion of time spent at the left screen region, for each priority level presented in both free-viewing (Panel A) and fixed-viewing (Panel B) conditions. Black bold lines indicate the average proportion of time spent looking at the left screen region across all 33 participants. Error bars indicate 95% confidence intervals based on Morey (2008). Grey lines indicate proportion of time spent looking at the left screen region for each participant individually.

The finding that participants in the free-viewing condition spent more time looking at a screen region that was more likely to be probed is further supported by the analysis of the mean horizontal distance of eye gaze from the centre (i.e. a + sign suggests leftward movement from the centre). Specifically, participants fixated further left from the centre when the left screen region was probed with a higher probability and further right from the centre when the left half was probed with a lower probability. The full LME model with priority and condition as fixed effects along with their interaction, fit these data significantly better than the null model, $\chi2$ (3) = 158.97, $p < .001$. In particular, there was a significant effect of priority of the left screen region on the mean horizontal distance from the centre, (b = 0.123,

SE = 0.008, t = 15.53, p < .001). That is, with increasing priority at the left screen region, the mean horizontal distance moved towards the left side from the centre. These findings provide further evidence that participants' gaze behaviour was influenced by priority, suggesting that participants were looking more at high versus low priority regions, particularly when eye movements were permitted. Furthermore, there was a significant effect of viewing condition on mean horizontal distance from the centre (b = 6.305, SE = 0.59, t = 10.68, p < .001) presumably because participants in the free-viewing condition were on average further away from the centre. Finally, there was a significant interaction between priority and viewing condition (b = -0.1203, SE = 0.011, t = -10.72, p < .001) as participants' distance from the centre in the free-viewing condition is likely to depend more on priority than in the fixed viewing condition.

Exploratory analyses

Similar to Experiment 2, the relation between the proportion of gaze time spent in the probed region and absolute tracking error was assessed, in both viewing conditions. The correlation for each individual participant was computed at a trial level, pooled over the three priority conditions. Figure 18 (Panel A) shows the distribution of participants' correlations in the free-viewing condition where 91% of them were negative. The mean correlation of -0.15 in the free-viewing condition was significantly different from 0, $t(32)$ = -6.03, p < .001. This indicates that in the free-viewing condition the more participants were looking in the probed screen region, the better their tracking performance (lower error). However, similar to the discussion made on findings of Experiment 1 and Experiment 2, taking into account the 'cued-factor' and the idea that most or even all of the measured variables in a dataset have non-zero correlations (Tibshirani, 2014), relevance and inferences from these tests need to be interpreted with caution. Figure 18 (Panel B) shows the distribution of correlations in the fixed-viewing condition where 48% of them were negative. It is clear that this distribution is much more symmetric around 0; indeed, the mean was -0.002 and was not significantly different from 0, $t(32) = -0.13$, $p = .895$.

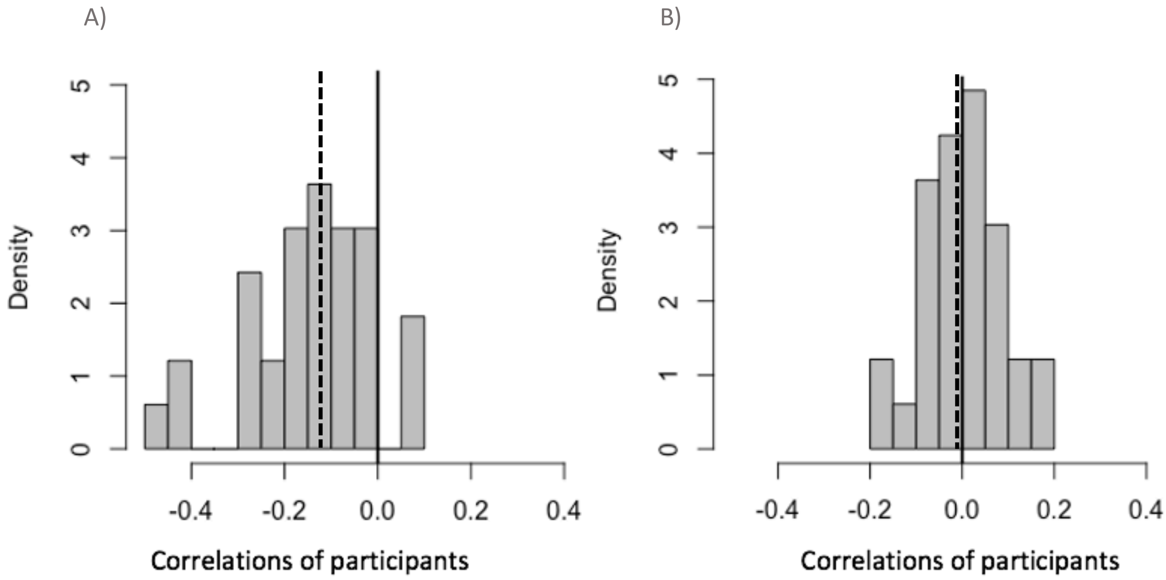


Figure 18. Histograms of correlations of individual participants between the proportion of time spent looking at the probed region and the tracking error (in degrees), in the free-viewing condition (Panel A) and the fixed-viewing condition (Panel B). The vertical bold lines indicate 0 correlation and the vertical dotted lines indicate the mean of all individual correlations.

Similar to Chapter 2, further exploratory analysis was conducted to ensure that the effect of unequal attention allocation is not a result of the data being averaged across trials, but is also evident on individual trials as well. This would show that participants do not completely withdrew their attention from the low priority region to solely track targets from the high priority region. Therefore this exploratory analysis looked at the proportion of time participants spent looking at each screen region *within* a trial for each priority condition. The between-trial probability matching account predicts that participants will spend almost all their time within a trial on one or the other region: for a given combination of region and priority, the distribution of the proportion of time spent in that region should have sharp peaks near 0 *and* 1, and very little density in between these extremes—in other words, a bimodal distribution. Within-trial probability matching predicts a unimodal distribution with a peak around the probability with which a region is probed. Figure 19 shows the proportion of time spent looking in the upper screen region in Experiment 2 (Panels A-C) and at the left screen region in the free-viewing condition of Experiment 3 (Panels D-F). These distributions are not consistent with the bimodal pattern predicted by between-trial probability matching, but they also do not completely fit the predicted pattern for within-trial probability matching. It is likely that there is a mixture of between and within-trial probability matching, where that mixture may result from between-participant differences in strategy or variations in strategy within participants over the course of the experiment. It is worth noting that participants' performance was above chance levels in all three priority conditions which increases the likelihood of participants tracking both high and low tracking regions in most trials.

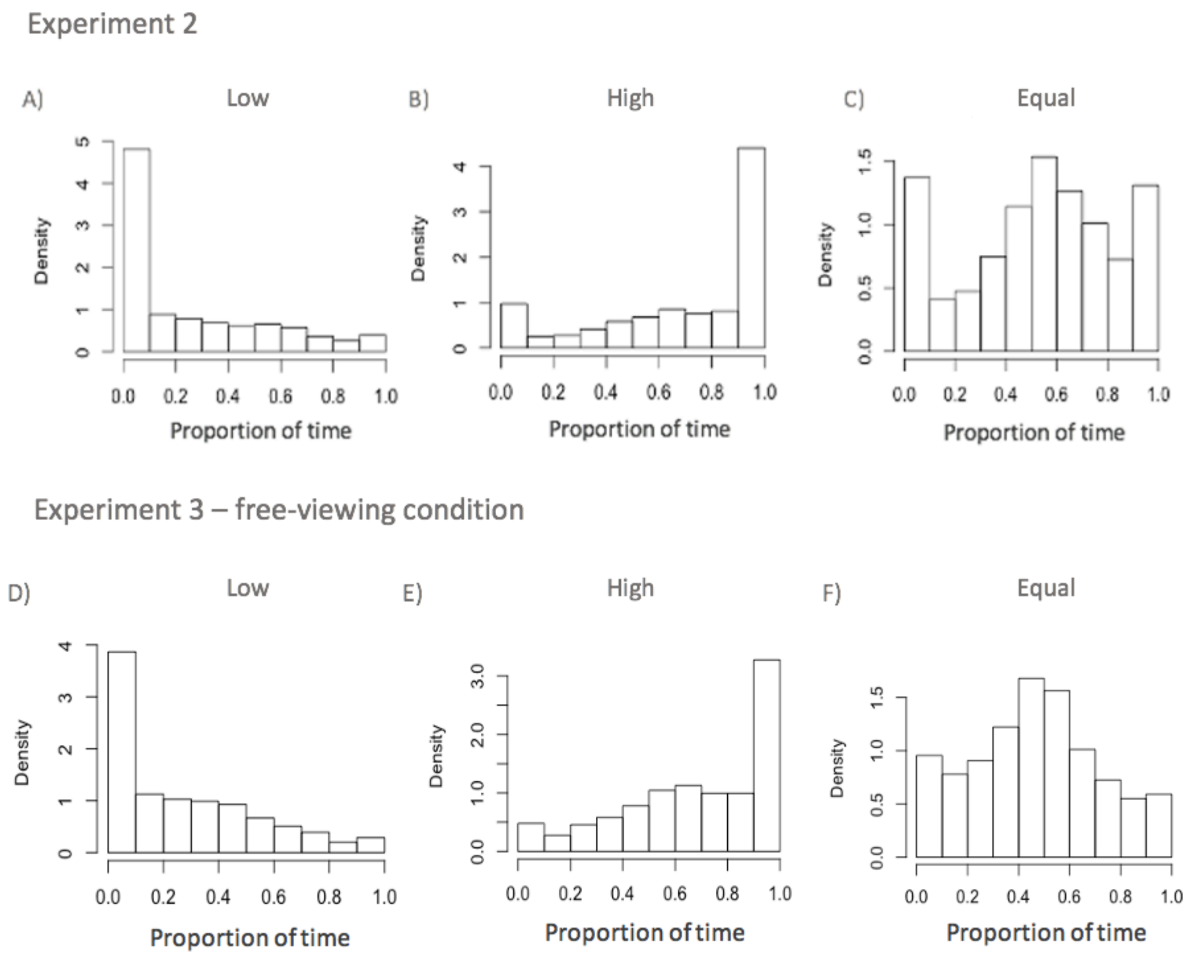


Figure 19. Panels A-C: Proportion of time spent looking at upper region of the screen on a trial level across all participants in Experiment 2, in low (Panel A), high (Panel B) and equal (Panel C) priority conditions. *Panels D-F*: Proportion of time spent looking at left region of the screen on a trial level across all participants in free-viewing condition in Experiment 3, in low (Panels D), high (Panel E) and equal (Panel F) priority conditions.

Taken together, the perceptual report and eye-tracking results of Experiment 3 provide further evidence for unequal attention allocation across screen regions, in both fixed- and free-viewing conditions. On the one hand, in the free-viewing condition, behavioural findings illustrate that participants have improved tracking accuracy as priority increased (Figure 14). Eye-tracking findings support this, showing an increased proportion of time looking at a high priority screen region (Figure 17) and greater distance from the vertical midline towards the high priority side as the priority presented in that region increased. These findings indicate that participants were allocating their attention unevenly across screen regions, based on the probability of a probe occurring in that region, supporting the results of Experiment 2. On the other hand, in the fixed-viewing condition, as participants fixated at the centre, roughly an equal proportion of their eye gaze was spent on each screen region. Interestingly, even with this eye movement pattern, which is more concentrated around the centre, participants' tracking performance improved as priority increased (Figure 14). Interestingly, the overall best performer across the two viewing conditions seems to be a member of the fixed-viewing condition (Figure 4), something which further highlights the possibility of successfully dividing your attention across two regions in an unequal manner using covert vision. This indicates that even without eye movements and by relying exclusively on peripheral vision, unequal attention allocation is still possible yet, only to a certain extent. Similar tracking performance was observed in the equal and high priority conditions in the fixed-viewing condition, suggesting that with covert attention, unequal attention allocation is possible in a less fine-grained manner compared to when foveal vision is employed (Figure 14). Overall, the findings of Experiment 3 suggest that eye movements play a causal, albeit modest, role in improving perceptual performance in the high priority region.

3.5 Discussion

The aim of the current Chapter was to investigate unequal attention allocation across two distinct regions and the extent to which this relies on eye movements (i.e. overt attention). Taken together, the findings of Experiment 2 and 3 indicate that participants prioritised attentional tracking in some regions versus others, in an unequal and graded manner such that as priority of a screen region increased, participants allocated more attention to that region. In particular, tracking accuracy improved with increasing probability of a region being probed and participants fixated more in the high priority region. Participants in both experiments were even found to allocate their attention between the two screen regions proportionally based on the priority of each region. In particular, roughly 70% of their time was spent on the high priority regions, 50% of their time was spent on the equal priority regions, and about 30% of their time was spent on the low priority region. This finding is reminiscent of probability matching (Eriksen & Yeh, 1985) and supports the idea that participants devoted the majority of their attention to the high priority region, but did not completely neglect the low priority regions. Evidence of goal-directed unequal allocation of attention was also obtained under the fixed-viewing condition of Experiment 3, where moving objects were tracked solely with peripheral vision. This finding indicates that unequal attention allocation is possible without eye movements, although priority had a greater and more fine-grained effect on tracking performance in the free-viewing condition. Therefore, it is concluded that unequal attention allocation is possible even when relying on peripheral vision. Nonetheless, eye movements, when permitted, do improve tracking accuracy, as participants are able to fixate in the high priority region and get a more precise foveal view of moving targets (Landry et al., 2001).

Compared with Chapter 2 and results of similar analysis in past investigations (i.e. Crowe et al., 2019), one could argue that the proportion of guessing should be lower in both Experiments 2 and 3 of Chapter 3. However, the highest proportion of guessing can be explained by the highest overall tracking error observed in Chapter 3, compared to Chapter 2. Both the higher guessing rates and the worse tracking performance are attributed to the different demands of the two tasks which consequently result in different levels of difficulty. In particular, in the current modified MOT task in Chapter 3, participants did not know from the beginning of the trial which of the four objects in each screen region would be the target, i.e., which object they would be questioned about. Therefore, participants had to track all eight objects across the two regions, which may have well increased the difficulty of the current task compared to the task used in Chapter 2 and in Crowe et al. (2019), in which only two objects needed to be tracked among six distractors (as priority was associated with specific items and not with entire screen regions) and much lower tracking errors and proposition of guessing were observed. Increasing the number of targets to be tracked is one of the most important factors which increases tracking load in MOT tasks and hence increases task attentional demands and task difficulty (Intriligator & Cavanagh, 2001). Specifically, tracking eight objects is likely to exceed the capacity limits for most observers (typically estimated around four objects; Scholl et al., 2001) and hence result in compromised overall tracking performance (i.e. higher angular error in Chapter 3 compared to Chapter 2, across all priority conditions). To cope with the high tracking load it is possible that participants simply drop tracking of some objects, probably from the low priority region and focus primarily on tracking of objects in the high priority region. This explanation is supported by the increased guessing rates of participants in the low priority regions. Even if participants managed to track all four items from the high priority region for the majority of the duration of the trial, this is still more attentionally demanding than tracking only 2 targets like in the case of Experiment 1, which therefore explains the higher guessing rates and worse tracking performance in Chapter 3 compared to Chapter 2. Nevertheless, both perceptual performance as well as gaze measures warrant against complete dropping of *all* low priority targets as tracking accuracy is well above chance tracking performance and participants are found to spend a significant amount of time looking at low priority regions. Participants might have dropped tracking of *some* targets from the low priority regions yet, given that the priority is associated with the whole screen region and not individual targets, it is argued that dropping tracking of *some* targets in line with priority, is a form of unequal attention allocation.

The findings of the current experiments provide further support to existing literature demonstrating that top-down instructions can guide goal-directed attention allocation (Brockhoff & Huff, 2016) and can be used to manipulate attention allocation of observers in different MOT tasks (Crowe et al., 2019; Cohen et al., 2011; Fitousi, 2016; Miller & Bonnel, 1994; Yantis, 1992). It appears that attention can be allocated adaptively across objects in different regions of the visual field depending on task demands. Additionally, the findings of Experiment 3 are in line with the literature on the usefulness of peripheral vision (Vater et al., 2016, 2017a, 2017b) in attentional tracking, and extend this view by showing that covert attention can be allocated *unequally* between different tracking regions, although not in a very fine-grained manner. Nevertheless, the tracking advantage of foveal vision observed in the high priority condition of Experiment 3 suggests that overt attention is more effectively allocated unequally than covert attention. This is in line with past literature findings suggesting that performing direct movements, like gaze movements, towards targets enhances the resolution of visual information and hence improves attention allocation (Andersen et al., 2004; Knudsen, 2007).

It is worth noting that past findings on the use of overt and covert attention during tracking were obtained from traditional MOT tasks in which attention was, presumably, allocated equally to targets. Having established the plausibility of unequal attention allocation using both overt and covert attention in the current series of experiments, future work should investigate specific tracking strategies (Fehd & Seiffert, 2008, 2010; Zelinsky & Neider, 2008) used during *unequal* attention allocation to investigate *how* exactly observers distribute their attention unevenly across different targets or regions of the visual field. For example, rather than centroid tracking (fixating in at the centre of the mass of targets) participants might be biased off centroid towards higher priority targets.

From an applied point of view, the current modified MOT task allows for an investigation of *unequal* attention allocation, better reflecting situations outside of the laboratory where observers are required to allocate their attention unevenly between different targets or regions of the visual field (e.g. a goal keeper having to track movement of more than one player or a security guard having to track movement of multiple people in different CCTV monitoring screens). Specifically, in both sports (Abernethy et al., 2001; Ward et al., 2002) and driving (Deng et al, 2019; Kotseruba et al., 2016; Wong & Huang, 2013) settings, information in different locations can vary in importance so attention needs to be allocated unequally in order to make a good judgment. Insights into how effectively attention can be allocated across these regions is, therefore, potentially valuable in informing practice in professional tasks that require attention to be allocated across multiple regions in an unequal manner.

Findings regarding the use and efficacy of peripheral vision compared to foveal vision can be applied in the context of driving and sports as well, given that peripheral vision is extremely important in both settings. For instance, sports players are often found to focus their eye gaze on an anchor point located between different visual regions of interest and process information from each area using peripheral vision (Milazzo et al., 2016; Piras & Vickers, 2011; Vansteenkiste et al., 2014), while drivers are found to use their peripheral vision for hazard perception and maintaining lane position (Costa et al., 2018; Summala et al., 1996). Therefore, based on the plausibility of unequal attention allocation (see also Chen et al., 2013; Crowe et al., 2019; Liu et al., 2005) and the functionality of peripheral vision in detecting motion changes during MOT (Fehd & Seiffert, 2008, 2010; Vater et al., 2016, 2017a, 2017b; Zelinsky & Neider, 2008), gaze-strategy training programmes in sports and driving contexts can be designed more carefully by taking into consideration the different capabilities of the human visual system. Given that driving accidents have been associated with misallocation of visual attention (Dingus et al., 2006; Klauer et al., 2006; J. D. Lee, 2008) it is highly important to invest in improving visual attention skills of drivers to increase road safety.

An important consideration of the modified MOT task used in the current experiments is the identical nature of all moving objects (i.e. 8 identical discs), which is unlike real-world settings were the individual targets we are tracking all have unique identities. Future research should therefore examine the role of foveal and peripheral vision in unequal attention allocation in a MIT task, where individual objects will have unique identities (Oksama & Hyönä, 2008). For example, the current modified trajectory-tracking MOT task can be altered into a trajectory-tracking MIT task where images of real objects (Iordanescu et al., 2011; Oksama & Hyönä, 2016) could be used instead of black discs. Such an investigation would shed light on how different target properties, in terms of similarity structure and saliency, can influence tracking strategies used by observers when dividing their overt and covert attention unequally across targets with unique identities. Will the efficiency of unequal attention allocation be improved further presumably because uniqueness of targets would increase their saliency and make them easier to be tracked? Or would the ability for unequal attention allocation be compromised because the more complex properties of targets (e.g. unique features, colours and shapes) would increase memory and attention load of the task?

To conclude, the current Chapter provides evidence of unequal attention prioritisation of different tracking regions in a modified trajectory-tracking MOT task in a top-down fashion. Participants were found to prioritise attentional tracking in some regions versus others, in an unequal and graded manner such that as priority of a screen region increased, participants allocated more attention to it during tracking. These findings were obtained under both free-viewing and fixed-viewing conditions, indicating that unequal attention allocation is possible without eye movements. However, when permitted, eye movements improve accuracy, as participants are able to focus their gaze on the region with the highest priority. Having established the plausibility of unequal attention allocation using both overt and covert attention, this study offers an insight into the functional role of eye movements during attentional tracking. The incorporation of eye-tracking methods when investigating unequal attention allocation in future experiments should further clarify the current findings and shed light on *how* exactly attention is allocated across different targets or regions of the visual field.

Chapter 4 Unequal attention prioritisation of static targets

Work presented in this chapter will be submitted for publication to Cognitive Research: Principles & Implications. Apart from some minor edits, this chapter is presented as per the manuscript. VH was responsible for experiment design, programming and set-up, data collection and analysis as well as manuscript preparation. CK and CL, as primary and secondary PhD supervisors of VH, were responsible for supervising the study in all stages.

4.1 Chapter Summary

Having established participants' ability to unequally divide their attention to different moving targets and *regions* of the visual field in Chapter 2 and Chapter 3 respectively, Chapter 4 aimed to explore participants' ability to unequally prioritise search for different *static* targets versus others based on their different levels of significance. In many real-life contexts, observers are required to search for targets of enormous importance to the health and safety of the public yet, these targets can be often missed because they are rarely present (e.g. tumours in X-rays; dangerous items in airport security screenings) in a visual scene. This bias is referred to as the prevalence effect. Although some studies have attempted to eliminate this effect, most of these studies use *single*-target searches. The current series of experiments aimed to investigate whether an unequal reward pattern can be used to reduce the prevalence effect in a response time hybrid search task. During this task, participants had to simultaneously search for three different targets held in memory, where each target had a different level of priority (i.e. prevalence and/or reward) associated with it. As a first step towards achieving this aim, the basic target prevalence effect (Experiment 4) and reward effect (Experiment 5) were replicated in the current hybrid search paradigm. Subsequently, the interaction of prevalence and reward effect was explored (Experiments 6 and 7), testing whether and to what extent the prevalence effect can be diminished, eliminated or even reversed, through the manipulation of unequal (Experiment 6) or equal (Experiment 7) reward. In Experiment 6 reward was manipulated inversely to prevalence such that as the prevalence associated with a target increased, the reward associated with it decreased. To the contrary, In Experiment 7 the same reward was associated with all targets irrespective of their different prevalence levels. Experiments 6 and 7 provided further support for the robustness of the prevalence effect, although unequal rewards (Experiment 6) did diminish the prevalence effect to some extent compared to equal reward (Experiment 7). Overall, this series of experiments makes two important contributions: 1) participants are able to prioritise search for mental representations of some targets held in memory over others in an unequal and graded manner based on their assigned priority (i.e. prevalence and/or reward); 2) using the current magnitude of reward, prevalence has a stronger impact on hybrid visual search for multiple targets than reward value but can be influenced to some extent by an unequal reward pattern with high rewards assigned to lower prevalence targets. Current findings provide evidence for the flexible nature of our attentional resource while also have practical implications regarding ways in which prevalence effect can be diminished in real-life settings.

4.2 Introduction

4.2.1 Searching for multiple targets in everyday life

Visually searching for a target amongst distractors is a critical component of everyday life. Whether we are searching for a friend in the crowd or for a specific product in a supermarket aisle, we are constantly required to search for behaviourally relevant information among an immense stream of less relevant visual input. It is often the case that some or all of the visual features of the targets we are searching for are known in advance, resulting in a goal-directed search process being guided by these specific features (Eimer, 2014; 2015; Wolfe et al., 2007). Such mental representations of target features or objects that guide our attention during visual search are assumed to be held in visual working memory and have been described as attentional templates (Duncan & Humphreys, 1992) or top–down control settings (Desimone & Duncan, 1995; Folk et al., 1992).

Past literature findings have investigated differences between single-target and dual-target search, with results indicating quicker and more accurate performance of observers when searching for one versus two targets (Barrett & Zobay, 2014; Menneer et al., 2010; Mestry et al., 2017). This indicates that when searching for multiple targets, mental representations of different targets are in competition in visual working memory, and this can potentially result in prioritisation of the search for one target over another especially in cases where the two targets have different levels of importance (Bays & Husain, 2008; Ma et al., 2014; Ort & Olivers, 2020; Williams et al., 2019). It is therefore critical to investigate contexts of multiple target search (i.e. searching for multiple targets in a given display) or multiple hybrid search (i.e. searching for an instance of any of several possible targets held in memory) where observers are required to search for more than two targets, something which has been largely overlooked in the prevalence literature (Ort & Olivers, 2020). Whether participants will be able to prioritize search of different targets unequally and in a graded manner, based on their associated level of priority of each target, is an open question.

Even though simultaneously searching for multiple targets comes at a cost of both the response time and accuracy of the search (Barrett & Zobay, 2014; Menneer et al., 2010;

Mestry et al., 2017) in many real-life cases observers are able to successfully search for hundreds of items at the same time, like in the case of airport security screening for dangerous items or searching on medical X-rays for tumors. In such cases not all targets can be held in visual working memory and observers are thought to perform a hybrid search, a combination of visual search and memory search, which allows them to effectively search for hundreds of targets (Wolfe, 2012). For instance, searching for threads in airport security screening could start with a categorical visual search for ‘fluids’ or ‘metal objects’, followed by a more detailed memory search, done solely on objects which pass the initial categorical search.

Apart from the number of targets to be searched for, their prevalence is another factor which influences visual search performance of observers. In particular, when we are searching for relatively rare targets it can be a challenging process. Take, the aforementioned examples of airport security X-rays for potentially dangerous objects in luggage (e.g. guns, knives, explosive devices) and medical X-ray screening tasks for tumours (e.g. mammography) or cytopathology screening (‘Pap tests’). The likelihood of finding a dangerous item in airport security screenings is relatively low (Rubinstein, 2001), while only around 1% of medical X-ray cases involve a tumour (Fenton et al., 2007; Gur et al., 2004; Smith & Turnbull, 1997; Breast Cancer Surveillance Consortium, 2009). While these events are rare, they are extremely important for security and health. The rare occurrence of such serious items decreases the efficiency with which they can be detected. This is referred to as the prevalence effect, which describes a cognitive bias towards detecting more quickly and efficiently objects that appear more frequently (high prevalence) in the visual field over objects that appear less frequently (low prevalence; Wolfe et al., 2005; Wolfe et al., 2007; Schwark et al., 2012; Mitroff & Biggs, 2014).

The prevalence effect was demonstrated by Wolfe et al. (2005) who conducted an artificial baggage screening task where participants were presented with 'tools' as targets on a noisy background, at different levels of prevalence (i.e. 1%, 10%, 50%). They showed that participants often miss targets that are rarely present, but that the probability of such 'miss errors' decreased as target prevalence increased (Wolfe et al., 2005; Wolfe et al., 2007). There is considerable evidence for the prevalence effect outside of the laboratory setting (Horowitz, 2017), in clinical (Evans et al., 2013; Gandomkar & Mello-Thoms, 2019; Berlin, 1994), security (Wolfe et al., 2013; Fishel et al., 2015) and driving (Beanland et al., 2014) contexts (although see Clark et al., 2012; Hättenschwiler et al., 2019). In particular, Evans et al., (2013) tested expert mammographers in a real world clinical setting during breast cancer screening checks and found that indeed, experts missed a much higher number of tumours in low prevalence conditions compared to high prevalence conditions. Similarly, newly trained Transportation Security Administration (TSA) officers were found to miss threat items of low prevalence during search for potentially dangerous objects in simulated airport security screening (Wolfe et al., 2013). Beanland et al., (2014) investigated the prevalence effect in a driving context using a driving simulation test of visual search with target vehicles being either motorcycles or buses. Results indicated that drivers detected high-prevalence vehicles faster than low-prevalence vehicles. Across all of these contexts, it appears that continuous performance assessment and training of professional visual search operators can improve their visual search efficiency for low-prevalence targets (Biggs et al., 2013, 2018; Biggs & Mitroff, 2014; Buser et al., 2020; Meuter & Lacherez, 2016; Mitroff et al., 2018; Nakashima et al., 2013; Spain et al., 2017). Given the important implications of the prevalence effect in real-life contexts, vision researchers have recently started to investigate other ways to overcome the prevalence effect, one of which is by offering rewards.

4.2.2 Factors influencing prevalence effect

Rich et al. (2008) argued that the nature of the search and the type of stimuli used, can influence the existence and magnitude of the prevalence effect. For instance, in a spatial configuration search, ‘miss’ errors were found to be a result of ending the search prematurely, while in a feature search task, ‘miss’ errors were more likely to be motor response errors. Other potential factors that can influence participants susceptibility to the prevalence effect include potential failures of perception (Godwin et al., 2014; Hout et al., 2015), low saliency of targets compared to distractors (Biggs et al., 2014), as well as past experiences and history of previous trials (Ishibashi et al., 2012; Lau & Huang, 2010). Vigilance of observers to low-prevalence targets has been found to increase when they were provided with object-based auditory-visual enhancements (e.g. playing a gun sound when a low-prevalence target was a gun facilitated reaction in both target-present and target-absent trials; Iordanescu et al., 2011) or when rare target were exogenously cued with valid colour or spatial cues (Russell & Kunar, 2012). Image segmentation has also been found to attenuate the prevalence effect in simulated cell slide pathology task (Forlines & Balakrishnan, 2009; but also see Kunar et al., 2010). On the contrary, providing eye movement feedback (i.e. informing participants about screen regions that were not inspected during their search) was not found to improve vigilance of observers to low-prevalent targets (Drew & Williams, 2017; Peltier & Becker, 2017a), yet explicit false feedback regarding participants’ perceived number of misses, was indeed effective (Schwark et al., 2012). This indicates that changing participants’ perceived number of misses, shifts the criterion formed by participants during the task, further supporting the argument of (Wolfe et al., 2007) on the existence of a decision criterion which causes ‘miss’ errors for low-prevalent targets.

There is a considerable amount of research investigating individual cognitive differences of participants which might influence their performance during visual search tasks and their susceptibility to the prevalence effect. Working memory has been found to predict selection and identification errors in visual search (Peltier & Becker, 2017a). Schwark et al. (2013) found that working memory capacity correlated significantly with the ability of participants to detect low-prevalence targets. Particularly, observers with high WM capacity were more persistent in their searchers than those with lower working memory capacity, as indicated by their prolonged target-absent responses in trials with infrequent targets. Working memory capacity, vigilance, attentional control and level of extroversion have all been identified as significant predictors of low prevalence search accuracy (Peltier & Becker, 2017b). Regarding colour targets in dynamic visual search in particular, Muhl-Richardson et al. (2018) found that verbal and spatial working memory capacity as well as intolerance to uncertainty significantly correlated with predictive monitoring for targets.

4.2.3 Efforts made to ameliorate the prevalence effect

Cognitive scientists have recently started to investigate potential ways to eliminate or even reverse the prevalence effect. For instance, Kunar et al. (2021) compared visual search performance of participants in 'double reading' versus 'single reading' procedures in a laboratory mammograph task. It was found that asking participants to perform the task *in pairs* led to a significant decrease of miss error rates compared to the *single* reading condition. Additionally, Fleck et al. (2010) used a different technique to ameliorate for prevalence effect in a classic target detection task, where half of the participants were allowed to correct their search and half not. Results indicated that when given the chance to correct last search, miss error rates decreased in low prevalent conditions (for contradictory findings see Van Wert et al., 2009). Taylor et al. (2021) managed to ameliorate the prevalence effect by asking participants to perform a similarity search (i.e. to identify any item most similar to the desired target) instead of performing a typical visual search task where participants are asked to search for presence or absence of items. Alternatively, Menneer et al. (2007) found that a divided effort strategy where different observers search for different target types can significantly decrease miss error rates in low prevalence conditions compared to asking observers to search for two or more different type of items simultaneously.

Although some of the attempts to ameliorate the prevalence effect have been found successful to some extent for use in the laboratory setting, this effect is generally seen as a 'stubborn' source of errors (Wolfe et al., 2007) which is hard to control, especially in real-life settings. This is because any potential strategy to reduce it needs to be both financially and practically feasible. For instance, giving TSA officers time to correct their search during the luggage x-ray screening can make airport security process more time consuming and cause severe security queues at the airports. Similarly, putting two TSA officers per screen to perform the luggage screening checks might significantly increase the financial burden for the airport companies. Therefore, any potential strategy employed for ameliorating for the prevalence effect needs to be adopted with caution, with practical and financial considerations being made.

What is more, the majority of investigations on how to ameliorate the prevalence effect primarily involved either single- or dual-target search tasks (Fleck et al., 2010; Menneer et al., 2007). Although the prevalence effect has generally been explored during multiple target search and hybrid target search (Biggs et al., 2014; Kunar et al., 2017; Wolfe et al., 2007; Wolfe et al., 2018), not a lot of studies have examined *ways to control* for this effect in visual search tasks with multiple targets. Such an investigation would offer a better reflection of real-life settings where observers are required to simultaneously search for multiple targets held in memory in a display or low prevalence targets (e.g. during airport security screening TSA officers search for a range of different rare items like knives, scissors, guns, explosives, blades and so on).

4.2.4 Using reward to ameliorate the prevalence effect

As previously stated in this thesis, value is an important source of guidance during attention allocation and visual search (Anderson et al., 2011b; Anderson & Yantis, 2012) with its important role being acknowledge by the latest Guided Search model 6.0 of Wolfe (2021). Offering a reward for detecting certain targets in visual search can direct more attention to them, improving visual search performance for those targets compared to the unrewarded or punished targets (Kiss et al., 2009; Krebs et al., 2010; Serences, 2008; Gong et al., 2016). This beneficial effect of reward has been observed when simple visual features (Hickey et al., 2011; Anderson et al., 2011b; a; Anderson & Yantis, 2012; Laurent et al., 2015; Theeuwes & Belopolsky, 2012), locations (Hickey et al., 2014; Chelazzi et al., 2014) or complex objects (Hickey et al., 2015; Hickey & Peelen, 2015) are rewarded.

A few studies have investigated the influence of reward on prevalence effects and whether the detectability of a rare target can be enhanced by increasing the reward associated with it (Navalpakkam et al., 2009; Won & Leber, 2016; Clark & Gilchrist, 2018). For instance, Navalpakkam et al. (2009) investigated whether changing the reward outcomes in a simple visual search task with identical stimuli, can improve detection rates. They found that increasing the reward offered for correct target detection can restore detection performance for rare targets, suggesting that reward schemes might be useful to improve detection rates in real-life tasks (see also contradictory findings by Won & Leber, 2016; Clark & Gilchrist, 2018). Similarly, Navalpakkam et al. (2010) compared the impact of value and prevalence on visual search in a complex perceptual environment. They found that observers were influenced by both value and prevalence of targets in a manner consistent with the ideal (Bayesian) combination of these cues (i.e. participants combined both factors to maximize the expected reward within each trial).

In real-life contexts, it is often the case that different items have different levels of importance associated with them (e.g. detecting a knife or gun in airport security screening is of much higher importance than detecting a liquid bottle). As a result, investigations of the interaction between prevalence and reward value should involve an *unequal reward pattern* such that prevalence of different targets is inversely related to the value associated with them. Wolfe et al. (2018) conducted a study looking at the impact of unequal value on the prevalence effect using a hybrid foraging task with multiple instances of multiple targets. Interestingly, in a condition where both value and prevalence were inversely related, participants showed a preference towards collecting the most highly valued items, irrespective of their prevalence. This suggests that prioritisation of multiple targets in visual search may be malleable through reward manipulation.

4.2.5 Aims of Chapter 4

The current series of experiments aimed to investigate whether an unequal reward pattern can be used to ameliorate the prevalence effect in a response time hybrid search task and cause participants to prioritise search for some targets versus others. During this task, participants had to simultaneously search for three different targets, where each target had a different level of 'priority' (i.e. prevalence and/or reward) associated with it. As a first step towards achieving this aim, the basic target prevalence effect (Experiment 4) and reward effect (Experiment 5) were replicated in a hybrid search paradigm with multiple targets. Subsequently, the interaction of prevalence and reward effect was explored (Experiments 6 and 7), testing whether and to what extent the prevalence effect can be diminished, eliminated or even reversed, through the manipulation of reward. Experiments 6 and 7 provided further support for the robustness of the prevalence effect, although unequal rewards did diminish the prevalence effect to some extent. Overall, this series of experiments makes two important contributions: 1) participants are able to prioritise search for mental representations of some targets over others in an unequal and graded manner based on their assigned priority (i.e. prevalence and/or reward); 2) using the current magnitude of reward, prevalence has a stronger impact on visual search than reward value but can be influenced to some extent by an unequal reward pattern with high rewards assigned to lower prevalence targets.

4.2.6 General Method

Openness of data: Each of the experiments were pre-registered on the Open Science Framework. Pre-registration information, the code for running the experiments, data and analysis scripts as well as stimuli used can be found on the OSF (Experiment 4: https://osf.io/cbueg/; Experiment 5: https://osf.io/gnjbx/; Experiment 6: https://osf.io/hrftb/; Experiment 7: https://osf.io/a3729/). All experiments reported here were granted ethical approval from the School of Psychological Science Research Ethics

Committee at the University of Bristol. All experiments were conducted according to the revised Declaration of Helsinki (2013).

Participants. Participants were recruited through the Prolific platform for online participant recruitment (https://www.prolific.co) over the period of mid to late 2021. They were paid £4 each for their participation. Previous lab-based studies involved sample sizes of around 18 participants (Clark & Gilchrist, 2018; Wolfe et al., 2007). Since this Chapter constitutes of a series of online experiments, data was expected to be noisier, so this number was doubled and data from 36 participants was collected for each experiment. In order to ensure that this sample size gave us enough power for the current task, a power calculation in R was performed using the SIMR package suitable for an LME design (P. Green & Macleod, 2016). With an effect size of priority of 0.25 (derived from Experiment 4), a sample of 36 participants gives us at least 99% power of detecting a similar effect at an alpha of .05. Inclusion criteria for participation in the study included self-reported normal or corrected-to-normal vision and age between 16-35 years.

Materials. A hybrid search task with multiple targets was programmed on Psychopy Builder (https://www.psychopy.org ; (Peirce et al., 2019) and was run online on Pavlovia (https://pavlovia.org) on participants' personal computers. On a typical 13" laptop monitor with a screen resolution 1,024 x 768 and viewing distance of 55 cm, one pixel corresponded to 0.02˚ of visual angle. Stimuli size is given based on this resolution and viewing distance while size in PsychoPy height units is also reported. Eleven items were chosen that included portable items that one can find at home (i.e. a pair of shoes, a cup, a backpack, a TV, a tape, a kettle, a helmet, a radio, a calculator, a cooking pot and a hair brush). The items' bounding box was square with sides of 1.57˚ of visual angle (0.1 height units). The same 11 items were viewed by all participants. For any one participant, three of these items were randomly chosen as targets of different prevalence and the remaining 8 items were distractors. On a given trial, there were 8 items presented on the display (see Figure 20, Panel D for an example); in target-present trials, these items included 1 target and 7 randomly chosen distractors, whereas in target-absent trials, these items included all 8 distractors. The centres of the 8 items were evenly placed along the circumference of a circle with radius 6.28˚ of visual angle (0.4 height units), such that all items were placed at an equal distance from the centre (i.e. centre of the screen was the centre of the circle of stimuli).

Procedure. Participants completed one testing session online, which lasted around 30 minutes. Participants had to remember three different targets throughout the experiment and each of these targets was associated with a different level of prevalence and/or reward. These targets were randomly assigned to every participant but remained the same for the whole duration of the experiment. Participants were presented with these three targets at the beginning of every block as a reminder to ensure that they were successfully remembering the identity of their three targets throughout the task. On every trial, participants were presented with a central fixation cross of size 0.47˚ of visual angle (0.03 height units) for 1.5 seconds before the stimulus of the 8 different items was presented. Participants had to detect if any one of the three targets (high, middle and low priority) was present or not and give a target-present ('A' key) or target-absent ('L' key) response as quickly as possible. Only one of these targets was present in each target-present trial. In order to ensure that participants had learned their items well enough and were actually detecting a target and were not just giving a random response, in Experiment 4, if participants gave a target-present response, they were presented with a second display of consecutive numbers from 1 to 8, of size 1.41˚ of visual angle (0.09 height units). Each one of these numbers was centred on the location where each item had previously been presented. Participants had to respond with the equivalent number key press to state in which particular location they detected the target. If they gave a target-absent response, then they would proceed straight to the next trial. Given that in Experiment 4, participants successfully located their target on more than 90% of the trials on average across all priority conditions, it was assumed that they successfully remembered the identity of their targets and were not merely giving a random response. Since the plausibility to successfully remember the identity of three targets in this task for the duration of the whole experiment was established in Experiment 4, in the subsequent experiments of this series (i.e. in Experiments 5-7), this target localisation screen was randomly presented 5 times in each block. The order of trial types was randomised within each block for every participant. Short breaks were allowed between blocks.

Figure 20. Panels A-C: A visual example of the instructions given to the participants in Experiments 4 to 7, regarding which three targets they would have to search for in the display together with their associated probabilities of appearing and/or reward associated with each. Panel D: An example of the stimuli display during an experimental trial.

Analysis plan. Linear Mixed Effects models (LMEs) (Baayen et al., 2008; Barr et al., 2013) and mixed-effect logistic regression models were used to analyse response time and accuracy data respectively, using the lme4 package (Bates et al., 2015) for the R computing environment (R Development Core Team, 2015). For all four experiments, at the initial stage of analysis, four different models were fit, each with a different structure and they were all compared based on their AIC weight values in order to select the "best" (in terms of the trade-off between goodness of fit and parameter count) model structure for statistical inference. Table 1 outlines the different models which were explored, for the analysis of both response time and accuracy along with their AIC weights (Wagenmakers & Farrell, 2004) for Experiments 4-7. Model 1 was the null model which included only a random-intercept for participants and identity, without priority (prevalence and/or reward) being considered. Model 2 included priority (prevalence and/or reward) as a fixed effect and a random-intercept for participants and identity. Model 3 included random- intercepts for participants and identity as well as priority (prevalence and/or reward) as fixed effect and as a random slope for participants. Model 4 was the maximal model that included random-intercept for both participants and identity as well as priority (prevalence and/or reward) as a fixed effect and as a random slope by both participants and identity. Results from the model with the highest AIC weight value are reported in the results section of each experiment (Burnham & Anderson, 2004). All inferences made from the findings of each experiment are based on the winning model.

Given the use of natural images and the random assignment of targets/distractors to different participants, it is important to account for any variance in performance induced by variations in the detectability of the different objects. Therefore, data were not aggregated across trials.

[5] For both response time and accuracy measures, data was analysed on a trial level. In Experiments 4, 5 and 7, priority (i.e. prevalence or reward) was entered as a predictor factor with low priority condition as the reference category. For Experiments 6, where both prevalence and reward were manipulated, the predictor was referred to as the 'status' of targets. Target status was entered as a factor with low prevalence/high reward condition as the reference category. In both LME (i.e. response time data) and multiple logistic regression (i.e. accuracy data) analyses sliding differences (i.e. repeated) contrasts was used instead of default treatment contrasts in order to explore differences across the three different levels of priority. Using sliding differences contrasts, the analyses explore differences between the reference category (i.e. low priority) and the second (i.e. middle priority) category as well as differences between the second category (i.e. middle priority) and third category (i.e. high priority). For each measure, fixed effect estimates for each prevalence level are reported from the chosen model. The same analysis plan and model structure was used for all four experiments.

For the response time data, restricted likelihood and Nelder-Mead optimisation was used and response time of participants in correct target-present trials was entered as the dependent variable. To deal with the skewness of the response time data and following results of the Box-Cox (Box & Cox, 1964) test, a reciprocal transformation was applied (only for the purpose of statistical analyses; descriptive statistics and figures are based on the untransformed data). Accuracy of the present/absent response in target-present trials was analysed using a mixed-effects logistic regression and proportion of miss errors of participants in correct target-present trials was entered as the dependent variable. BOBYQA

[5] Data was analysed aggregated across trials and similar effects are observed across all four Experiments.

optimisation was used. Correct responses were coded with 0 and incorrect responses were coded with 1.

4.3 Experiment 4

Experiment 4 aimed to replicate the basic target prevalence effect in a hybrid search task with multiple targets. Priority was manipulated in terms of prevalence, with participants having to hold mental templates of three different targets with different degrees of prevalence: high (70% occurrence when a target was present), medium (20% occurrence) and low (10% occurrence) prevalence. This allowed us to test whether participants were able to prioritise search for different targets in an unequal and graded manner in accordance to their priority level (i.e. prevalence in the case of this experiment) or whether prioritisation would follow an all-or-nothing pattern with some (or even all) target templates prioritised to the same degree.

4.3.1 Method

Participants. 36 participants (14 female) took part in the experiment, with age (M ± SD), 24.1 ± 3.9 years.

Design. The within-subjects priority factor of prevalence was manipulated across three levels (Low: 10%, Middle: 20% and High: 70%).

Procedure. Participants performed 20 practice trials to get familiar with the computer task and then 400 experimental trials. Half the trials were target-present trials and half were target-absent trials. These 400 experimental trials were divided into 5 blocks of 80 trials each (i.e. 40 target-present and 40 target-absent trials in every block). Each block contained an equal number of trial types: 28 trials (70%) where a high prevalence target was presented, 8 trials (20%) where a medium prevalence target was presented, 4 trials (10%) where a low prevalence target was presented and 40 trials where 8 distractors and no target were presented. At the beginning of every block, participants were presented with the templates of the three targets they would have to search for in the visual display, and the associated probabilities of each of the three targets appearing (i.e. low: 10%, middle 20%, high: 70%; see Figure 20, Panel A).

4.3.2 Results and Discussion

Trials in which participants had a response time less than 200ms or more than 6 seconds were excluded from the analysis. Based on this exclusion criterion, 1.8% of trials were excluded. Participants who had more than 10% of their trials excluded, were removed from the analysis. Based on this exclusion criterion, 2 participants were excluded from the total of 36 participants. Because the pre-registration did not include any exclusion criteria, data was also analysed *before* exclusion and a qualitatively similar pattern of results to that reported here was obtained. In the subsequent experiments, the same exclusion criteria were registered and applied. To ensure comprehensible comparison between findings of all three experiments, reported results of Experiment 4, include data analysed *after* application of the exclusion criteria.

Out of the four different models explored in the analysis, Model 3 was found to capture the data from Experiment 4 best, for both response time and accuracy, as seen in Table 1. This model included random intercepts for participants and target identity as well as prevalence as fixed effect and as a random slope for participants. Results from this model are reported for each variable.

Table 1. AIC weight values for all models explored in Experiments 4-7.

	Models			
	1 (null)	2 (+ random intercept)	3 (+ random slope)	4 (maximal)
Response Time (LME analysis)				
Experiments				
4	0	0	**0.91**	0.09
5	0	0	**1**	0
6	0	0.16	**0.77**	0.08
7	0	**0.57**	0.42	0.01
Accuracy (Mixed effect logistic regression)				
Experiments				
4	0	0.07	**0.99**	0
5	0	0.06	**0.98**	0
6	0	0	**0.98**	0.02
7	0	0	**0.96**	0.04

Note. The model which best captures the data in each experiment and variable is the model with the highest AIC weight and is highlighted in bold.

Response Time analysis. Figure 21 (Panel A) indicates response time for hit (i.e. correct target-present trials) across all three prevalence levels or correct rejection (i.e. correct target-absent trials) across all three prevalence levels. As prevalence increased in target present trials, participants were significantly quicker at correctly identifying the target. Beta values reported in the response time analysis for all four experiments, are effect estimates for priority (prevalence and/or reward) and since priority in this series of experiments was analysed as a categorical factor (and not as a continues variable), an effect estimate is given for each of the three priority levels. Low prevalence is used as the reference category and sliding differences (i.e. repeated) contrasts was used (instead of default treatment contrasts) therefore, the analysis explores differences *between* the three categories. This means that the beta value for the middle priority offers an effect estimate for the middle priority condition, compared to the reference category (i.e. low priority) and the beta value for the high priority condition offers an effect estimate for the high priority condition, compared to the middle priority condition. The slowest response time was observed in the low prevalence condition (M = 1.28, SD = 0.68, b = 1.08, SE = 0.05, t = 20.09, p < .001), an intermediate response time was observed in middle prevalence condition (M = 1.14, SD = 0.66, b = 0.11, SE = 0.02, t = 4.56, p < .001) and the fastest response time was observed in high prevalence condition (M = 1.02, SD = 0.61, b = 0.14, SE = 0.02, t = 7.43, p < .001). The slowest average response time was observed in target-absent trials, in line with previous literature (Wolfe et al., 2005; Wolfe et al., 2010) showing that typically, response times are longer when no target is present, as participants have to visually search across all items.

Accuracy analysis. Figure 21 (Panel B) indicates participants proportion of errors across all trial types. In target-present trials these refer to miss errors, while in target-absent trials these refer to false alarms. It can be seen that as prevalence increases, participants' accuracy in target detection is improved as their miss errors in target-present trials decrease. Prevalence was found to have a significant effect on participant's accuracy, whereby the lowest accuracy was observed in the low prevalence condition (*log odds* = -3.67, SE = 0.26, z = -14.23, p < .001), an intermediate accuracy was observed in the middle prevalence condition (*log odds* = -1.01, SE = 0.33, z =-3.08, p = .002) and the highest accuracy was observed in the high prevalence condition (*log odds* = -1.12, *SE* = 0.29, *z* = -3.83, *p* < .001). Overall, the average proportion of miss errors across participants in target-present trials, decreased as prevalence increased (Figure 21, Panel B).

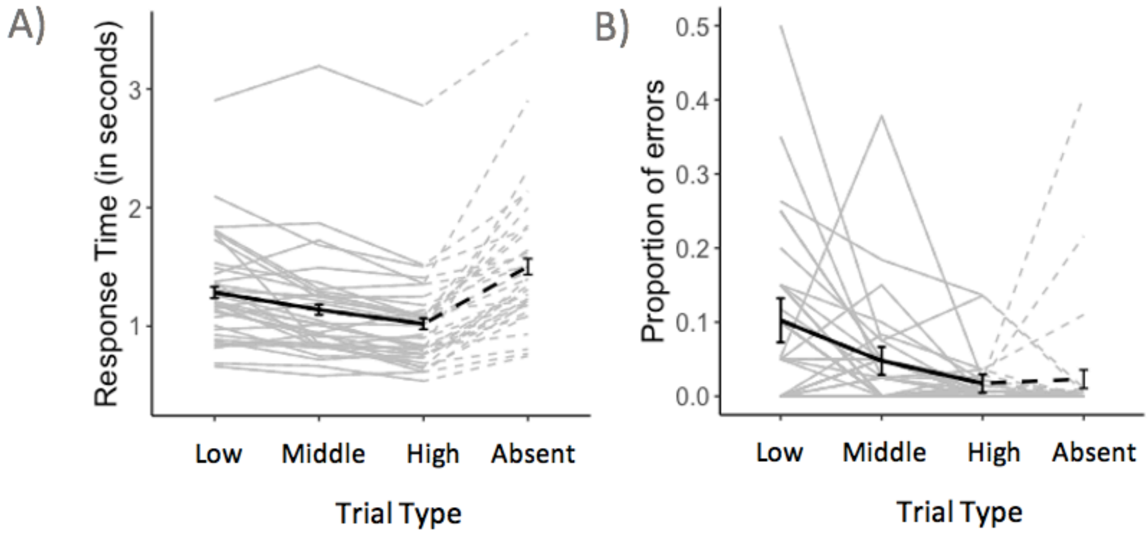


Figure 21. Panel A: Mean Response Time (in seconds) for all participants in target-present (i.e. low, middle and high prevalence) and target-absent trials, in Experiment 4. Panel B: Proportion of errors, for all participants in Experiment 4. In target-present trials (i.e. low, middle and high prevalence), these refer to miss errors whereas in target-absent trials these refer to false alarms. In both panels, black lines indicate mean measures across all participants while grey lines indicate individual data for each participant. Error bars indicate 95% within-subject confidence intervals based on Morey (2008).

Taken together, the results of Experiment 4, support the existence of the prevalence effect in the current hybrid search task, demonstrating that participants had higher response times and a higher proportion of misses when the target had a low compared to high prevalence. This is in line with previous literature suggesting that observers are quicker and more accurate in target detection, for high versus low prevalence targets (Wolfe et al., 2005; Wolfe et al., 2007; Clark & Gilchrist, 2018). Current results even extend past literature findings as they indicate that when searching for *multiple* targets, visual search performance of participants increases as prevalence increases, while past literature findings primarily involved the search of maximum two targets (Hout et al., 2015). This means that participants are capable to search for targets in an unequal and graded manner, prioritising search for some targets versus others depending on their associated levels of importance. One potential explanation for why participants are found to prioritise search for different targets based on their prevalence and not trying harder to search for all three targets to the same extent, is the difficulty of the task. During hybrid search for multiple targets, mental representations of different targets are in competition in visual working memory, and this can potentially result in prioritisation of the search for one target over another especially in cases where the two targets have different levels of importance based on top-down instructions (Bays & Husain, 2008; Ma et al., 2014; Ort & Olivers, 2020; Williams et al., 2019). Alternatively, given that participants were explicitly informed about the prevalence of different targets, it could be argued that they chose to prioritize search for the targets with the highest prevalence in order to improve their overall performance in the task and ensure that they would successfully find the target in the majority of trials. According to Clark and Gilchrist (2018) successfully finding a target during visual search task can be in itself rewarding, meaning that targets with a highest probability of being presented are associated with a higher intrinsic reward.

4.4 Experiment 5

Having established the prevalence effect in the current hybrid search task with multiple targets, the purpose of Experiment 5 was to investigate the influence of reward on target detection. In particular, this experiment aimed to replicate the basic effect of reward on target detection (Kiss et al., 2009; Krebs et al., 2010). In this experiment priority was manipulated in terms of the amount of reward received upon both accurate and quick target detection. Participants had to hold representations in memory of three different targets with different degrees of reward (i.e. high, medium and low reward). This allowed us to test whether participants were able to prioritise search for different targets in an unequal and graded manner in accordance to their priority level (i.e. reward in the case of this experiment) or whether prioritisation would follow an all-or-nothing pattern with some (or even all) target templates prioritised to the same degree.

4.4.1 Method

Participants. 36 participants (21 female) took part in the experiment, with age (M ± SD), 26.3 ± 4.3 years.

Design. The within subject priority factor of reward was manipulated across three levels (Low: 1 point, Middle: 2 points and High: 7 points).

Procedure. Participants performed 20 practice trials and 300 experimental trials. 150 of those were target-present trials and 150 of those were target-absent trials. Out of the 150 target-present trials, 50 contained the high reward target, 50 the middle reward target and 50 the low reward target (i.e. prevalence remained constant). These 300 experimental trials were divided into 5 blocks of 60 trials each with an equal number of each trial type. The order of trial types was randomised within each block for each participant. There were opportunities for breaks between blocks.

In both target-present trials and target-absent trials, if participants gave a correct and quick response, they would receive a reward, in points. These points were then translated to lottery tickets (1 point = 1 lottery ticket). At the end of every block participants were presented with the total number of tickets they had collected so far. Participants were told that three lottery tickets from all participants would be chosen at random, with the constraint that the tickets must belong to three different participants, and the three winners would receive £25 extra for their participation in the experiment. Therefore, the more tickets participants collected the higher their chance of winning. The response time benchmark for assigning reward was less than or equal to 1,000ms (this criterion was set to fall just below the average median response time of all participants in Experiment 4, which was 1,100ms).

At the beginning of every block, participants were presented with the images of the three targets they had to search for in the visual display, and the associated levels of reward in terms of points (see Figure 20, Panel B for an example). The colour of the text denoting the number of points for each target varied such that '7 points' was written in green colour, '2 points' was written in orange colour and '1 point' was written in red colour. In target-present trials, if participants received a reward they were presented with written feedback about the number of points they received (depending on which target was shown). The text colour used in the visual feedback was the same as the associated level of reward. In target-absent trials, if participants gave a correct and quick enough response, they also received a reward, that was equally likely to be low (1 point), medium (2 points) or high (7 points). This was done in order to motivate participants to pay attention to target-absent trials as well and discourage them from continuously giving target-present responses. In this case, the text colour used in the visual feedback was black. In both target-present and target-absent trials, along with the visual notification of their reward if a correct and quick reply was given, participants heard a 'coin drop' sound, notifying them that they have received points.

If participants gave an incorrect response in both target-present and target-absent trials, they were presented with a feedback screen notifying them that no reward had been received. In this case instead of the 'coin drop' sound participants heard a low frequency sine wave sound, notifying them about their incorrect response. If participants gave a correct but too slow response (i.e. greater than 1,000ms), they received no reward and they were presented with an written feedback that they were too slow and no feedback sound was played.

Visual and auditory feedback was available for participants for 1.5 seconds. Visual text feedback was located at the centre of the screen and was written in Times New Roman font with a size of 1.1˚ of visual angle (which corresponds to 0.07 height units). The actual volume of the sound participants heard, depended on the volume of their individual computers. However, the scale factor for sound feedback was set at 1, which means that the sound would play at the exact volume set on participants' computer. PsychoPy PTB audio library was chosen and audio latency priority was set at 4. Sounds for audio feedback were retrieved from an online sound-effect library (https://freesound.org/people/Bertrof/sounds/351565/).

4.4.2 Results and Discussion

The same exclusion criteria as Experiment 4 were applied, with the following exceptions. Given the presence of the temporal deadline for reward assignment (i.e. 1,000ms) in this Experiment, participants' responses were speeded up compared to Experiment 4 therefore, it was more appropriate to decrease the response time upper limit for exclusion which was now set to 4,000ms. 0.1% trials were excluded as too fast or too slow. No participants had more than 10% of their trials excluded. Because of the nature of this reward task, an additional exclusion criterion to Experiment 4 was applied regarding accuracy of participants. Based on participants' accuracy distribution, those with a hit rate below 2 SDs of the mean or a false alarm rate above 2 SDs of the mean were excluded from further analysis. Based on this exclusion criterion, three participants were excluded from the analysis (one participant had a hit rate below 2SDs of the mean and two participants had a false alarm rate above 2SDs of the mean).

Out of the four different models explored in the analysis, Model 3 again captures the data from Experiment 5 best, regarding both response time and accuracy measures, as seen in Table 1. This model included random intercepts for participants and identity as well as reward as fixed effect and as a random slope for participants. Results from this model are reported for each variable.

Response time analysis. Figure 22 (Panel A) shows the response time of participants in trials where they gave a correct hit or correct rejection. A main effect of reward on participants' response time was found, whereby the slowest response time was observed in low reward condition (M = 0.7, SD = 0.22, b = 1.58, SE = 0.05, t = 34.33, p < .001), an intermediate response time was observed in middle reward condition, although this contrast was not significant (M = 0.68, SD = 0.23, $b = 0.04$, $SE = 0.02$, $t = 1.64$, $p = .120$). The fastest response time was observed in high reward condition (M = 0.64, SD = 0.22, $b = 0.08$, $SE = 0.03$, $t = 2.95$, $p < .001$). This evidence suggests that as reward levels increased, response time decreased (Figure 22, Panel A). The slowest average response time was observed in target-absent trials, in line with previous literature (Wolfe et al., 2005; Wolfe et al., 2007).

Accuracy analysis. Figure 22 (Panel B) shows participants proportion of errors across all trial types. As reward increases, participants' accuracy in target detection is improved as their misses decrease. Findings indicated that reward had a significant effect on participant's accuracy, whereby the lowest accuracy was observed in the low reward condition (*log odds* = -1.69, $SE = 0.18$, $z = -9.22$, $p < .001$), an intermediate accuracy was observed in the middle reward condition (*log odds* = -0.43, $SE = 0.16$, $z = -2.75$, $p = .006$) and the highest accuracy was observed in the high reward condition (*log odds* = -0.22, $SE = 0.20$, $z = -1.09$, $p < .001$). As reward increased, participants' likelihood of making an error decreased (Figure 22, Panel B).

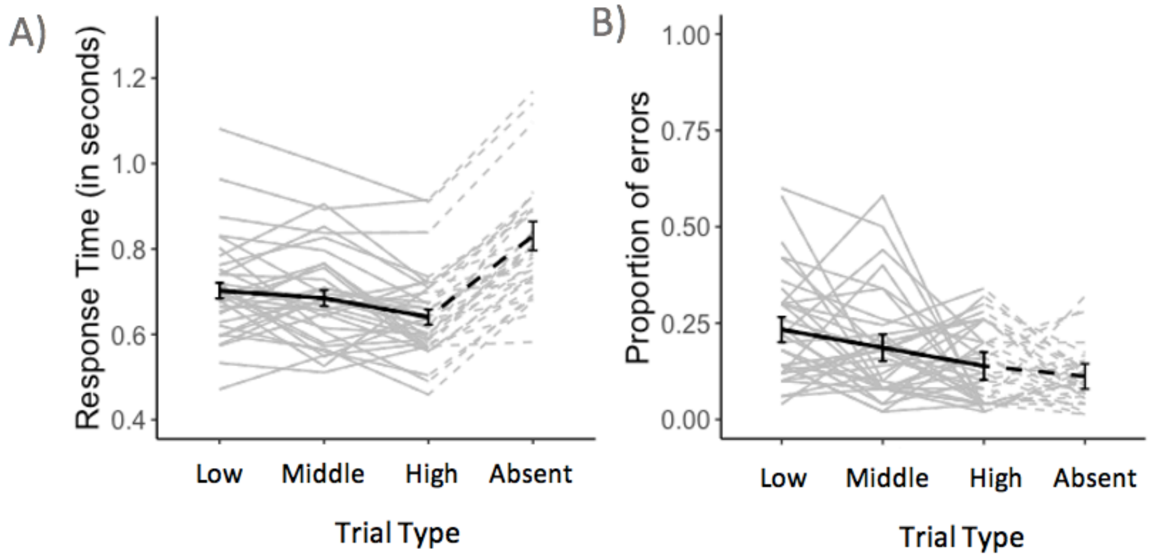


Figure 22. Panel A: Mean Response Time (in seconds) for all participants in target-present (i.e. low, middle and high reward) and target-absent trials, in Experiment 5. Panel B: Proportion of errors, for all participants in Experiment 5. In target-present trials (i.e. low, middle and high reward), these refer to miss errors whereas in target-absent trials these refer to false alarms. In both panels, black lines indicate mean measures across all participants while grey lines indicate individual data for each participant. Error bars indicate 95% within-subject confidence intervals based on Morey (2008).

The results of Experiment 5 support the prediction, that participants would have slower response times and fewer misses in identifying the target amongst distractors when this is associated with a higher versus lower reward. This is in line with previous literature suggesting that observers are quicker and more accurate in target detection as reward increases (Kiss et al., 2009; Krebs et al., 2010; Serences, 2008; Gong & Yang, 2016). The results of the current experiment support the claim that participants are able to prioritise visual search for some mental representations of targets versus others, in an unequal and graded manner according to the priority (i.e. reward) assigned to each.

4.5 Experiment 6

Having established the effects of prevalence (Experiment 4) and reward (Experiment 5) on target detection in the current hybrid search task, the aim of Experiment 6 was to combine both forms of priority to explore whether detection efficiency of low prevalence targets can be improved through reward. A few studies have investigated whether reward can improve detection of low prevalence targets, however, evidence is not yet conclusive regarding the extent to which reward can overcome or moderate the prevalence effect (Navalpakkam et al., 2009; Won & Leber, 2016; Clark & Gilchrist, 2018). To my knowledge limited investigations have been conducted where unequal reward is used to mitigate the prevalence effect (Wolfe et al., 2018). In the current experiment, reward was inversely related to the prevalence of a target such that as prevalence decreased reward increased. There were two distinct possible outcomes from the current study; a) *prevalence* would trump reward in which case reward would no longer influence performance at all and similar results to Experiment 4 would be expected or b) *reward* would modulate the prevalence effect in that the prevalence effect would get diminished, eliminated or even reversed. Consider the negative slope(s) relating response time and errors to prevalence. The question is: what happens with this slope in the case where reward is inversely related to prevalence? In the diminution scenario, reward would decrease the influence of prevalence on target detection but not to the extent that it would eliminate or even reverse its effect (negative slope). In the case of elimination, then the increase in reward for the low prevalence target would be exactly right to counteract its lower prevalence (approximately zero slope). Given the prevalence and reward values chosen in this experiment, this would suggest that participants are guided by expected value (the product of the probability of an event occurring and the magnitude of reward associated with it). In the scenario of complete reversal, then reward would trump prevalence (positive slope) and similar results to Experiment 5 would be expected.

4.5.1 Method

Participants. 36 participants (18 female) took part in the experiment, with age (M ± SD), 23.6 ± 3.6 years.

Design. Target status (i.e. prevalence/reward combination) was manipulated within subjects, across three levels: low prevalence/high reward, medium prevalence/medium reward and high prevalence/low reward.

Procedure. Participants were informed about the associated prevalence and reward of each target at the beginning of the experiment and before the start of each block as a reminder, similar to Experiments 4 and 5 (see Figure 20, Panel C for an example). Participants completed 20 practice trials followed by 400 experimental trials. Prevalence was manipulated in the same way as in Experiment 4 where out of 400 experimental trials, 200 were target-present and 200 were target absent. High prevalence targets were present on 70% of target-present trials, a medium prevalence target was present on 20% of target-present trials and a low prevalence target was present on 10% of target-present trials. The same visual and auditory reward cues were used as in Experiment 5, but in this case high reward was assigned to the low prevalence target, medium reward to the medium prevalence target and low reward to the high prevalence target. In target-absent trials, if participants gave a correct and quick enough response, they also received a reward. However, due to the different number of trials in Experiment 6 versus Experiment 5, in this case the amount of points gained was *almost* equally likely to be low, medium or high (i.e. 13 trials would be rewarded with 7 points, 13 trials would be rewarded with 1 point and 14 trials would be rewarded with 2 points).

4.5.2 Results and Discussion

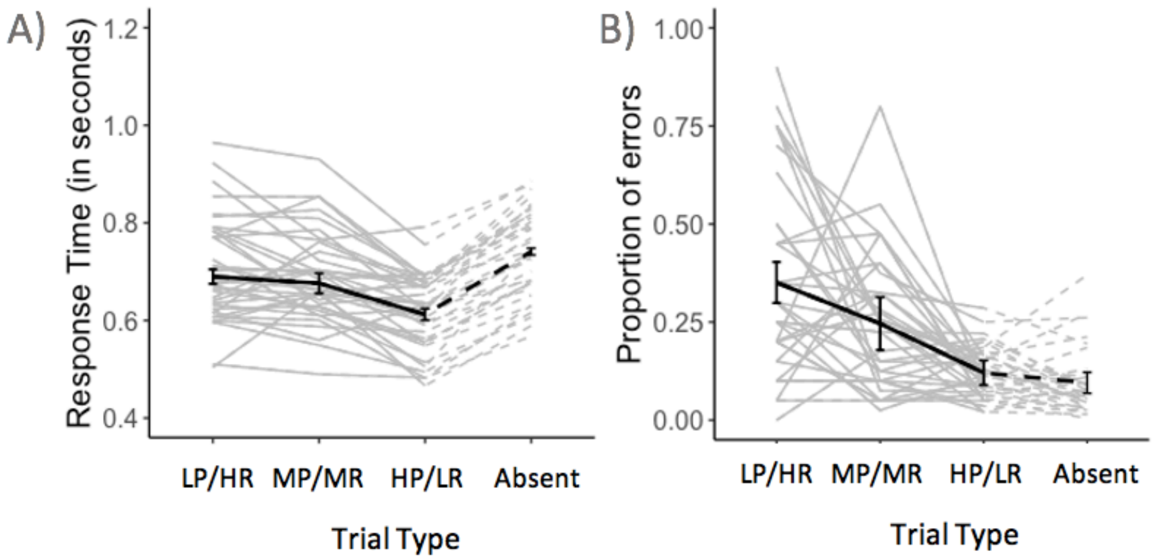
The same exclusion criteria as in Experiment 5 was applied. 0.1% of the trials were excluded as too fast or too slow. No participants had more than 10% of their trials excluded. Based on participants' accuracy distribution, those with a hit rate below 2 SDs of the mean and a false alarm rate above 2 SDs of the mean were excluded from the analysis. Based on this exclusion criterion, two participants were excluded from the analysis.

Out of the four different models explored in the analysis, Model 3 was found to best capture the data in Experiment 6, regarding both response time and accuracy measures, as seen in Table 1. This model included random intercepts for participants and identity as well as target status as fixed effect and as a random slope for participants. Results from this model are reported for each variable.

Response time analysis. Figure 23 (Panel A) indicates the response time of participants in trials where they gave a correct hit or correct rejection. As prevalence increased in target present trials, participants were significantly quicker at correctly detecting it, irrespective of the higher reward offered to low prevalence targets. A main effect of status on participants' response time was found, whereby the slowest response time was observed in low prevalence/high reward condition (M = 0.69, SD = 0.22, $b = 1.62$, $SE = 0.04$, $t = 38.19$, $p < .001$), an intermediate response time was observed in the medium prevalence/ medium reward condition (M = 0.67, SD = 0.23, $b = 0.07$, $SE = 0.03$, $t = 2.30$, $p = .029$) and the fastest response time was observed in the high prevalence/low reward condition (M = 0.61, SD = 0.19, $b = 0.16$, $SE = 0.02$, $t = 7.78$, $p < .001$). This evidence suggests that as prevalence levels increased, response time decreased (Figure 23, Panel A) similar to the effect of prevalence observed in Experiment 4, irrespective of the reward given in the current experiment. This suggests that reward did not moderate the effect of prevalence on target detection.

Accuracy analysis. Figure 23 (Panel B) shows the proportion of errors across all trial types. It can be seen that as prevalence increases, participants' errors in target detection decreases, irrespective of the higher reward associated with low prevalence targets. There was a main effect of target status on participants' accuracy, whereby the lowest accuracy was observed in the low prevalence/high reward condition (*log odds* = -1.39, $SE = 0.15$, $z = -9.32$, $p = .001$), an intermediate accuracy was observed in the medium prevalence/medium reward condition (*log odds* = -0.58, $SE = 0.258$, $z = -2.27$, $p = .024$) and the highest accuracy was observed in the high prevalence/low reward condition (*log odds* = -0.76, $SE = 0.19$, $z = -4.10$, $p < .001$). This indicates that as prevalence increased, participants' likelihood of making an error decreased, hence accuracy in target detection was improved, regardless of the reward assigned (Figure 23, Panel B).

Figure 23. Panel A: Mean Response Time (in seconds) for all participants in target-present (i.e. LP/HR, MP/MR, HP/LR) and target-absent trials, in Experiment 6. Panel B: Proportion of errors, for all participants in Experiment 6. In target-present trials (i.e. LP/HR, MP/MR, HP/LR), these refer to miss errors whereas in target-absent trials these refer to false alarms. In both



panels, black lines indicate mean measures across all participants while grey lines indicate individual data for each participant. Error bars indicate 95% within-subject confidence intervals based on Morey (2008).

Overall, both response time and accuracy measures in Experiment 6 suggest that with the current reward pattern in this hybrid search task, prevalence dominates reward. The results resemble closely those of Experiment 4: faster responding and fewer misses were observed as prevalence increased. However, faster response speed and more miss errors were observed in Experiment 6 versus Experiment 4 (Figure 21). It is important to note that

Experiment 6 differed from Experiment 4 due to the presence of a temporal deadline (if participants did not respond within 1,000ms they did not receive the reward) and the presence of a reward that varied with prevalence. Therefore, the increases in response speed and miss errors in Experiment 6 could be the result of one or both of these factors.

Due to these differences between Experiments 4 and 6, the current results do not allow us to make conclusive inferences on the actual impact reward had on the prevalence effect. It is possible that prevalence is found to be stronger than reward. However, the results do not rule out the scenario that reward diminishes prevalence, at least to a degree (i.e. diminution scenario), such that it does not lead to complete elimination or even reversal of the prevalence effect. As a result, it is critical to assess the prevalence effect in the presence of equal reward and the same time pressure that participants were under in Experiment 6. Such a manipulation makes for a cleaner test of the extent to which the prevalence effect may be modulated by unequal reward.

4.6 Experiment 7

The effect of *unequal reward* as a way of counteracting the effect of prevalence was of important interest in the current chapter. In Experiment 7 a *constant* reward was associated with all targets. Experiment 7 was designed as an attempt to equate for the presence of a temporal deadline and the presence of a reward. In this way, the conditions of the reward would become similar to those of Experiment 6, allowing for a cleaner assessment of the effect of unequal reward. Another way to investigate the effect of reward, would be to run Experiment 7 without the presence of any temporal deadline to directly compare it with Experiment 4 of this series. However, given the limited time that observers in real-life (e.g.

airport security screening, medical x-rays etc.) often have available to detect a low prevalence target during visual search, the decision to maintain an element of time pressure in Experiment 7 was taken, as this is thought to better reflect real-life settings and offer higher ecological validity to the experiment.

4.6.1 Method

Participants. 36 participants (24 female) took part in the experiment, with age (M ± SD), 23.5 ± 4.2 years.

Design. Target prevalence was manipulated within subjects across three levels (Low, Medium and High) as in Experiment 4. However, in this experiment a constant reward (i.e. number of points) was associated with all targets, unlike Experiment 4 in which no reward was used.

Procedure. Participants were informed about the associated prevalence of each target at the beginning of the experiment and before the start of each block as a reminder, as in previous experiments (see Figure 20, Panel A for an example). Participants completed 20 practice trials followed by 400 experimental trials. Out of which 200 were target-present and 200 were target absent. The three different targets participants had to search for in the visual display were associated with three levels of prevalence as in Experiments 4 and 6, such that the high prevalence target was presented on 70% of the trials, the medium prevalence target was presented on 20% of the trials and the low prevalence target was presented on 10% of the trials.

In the current experiment a constant reward of 2 points was given to the participants upon quick (i.e. less than 1 second) and accurate responding in both target-present and target-absent trials, as opposed to Experiment 6, where a larger reward was associated with low prevalence targets and less reward was associated with high prevalence targets. Visual and auditory feedback was presented to the participants in the same way as in Experiment 5 and 6, but in this case, the text colour used in the visual feedback was always black as there was only one reward level.

4.6.2 Results and Discussion

The same exclusion criteria as in Experiments 5 and 6 were applied. 0.2% of the trials were excluded as too fast or too slow. No participants had more than 10% of their trials excluded. Based on participants' accuracy distribution, those with a hit rate below 2 SDs of the mean and false alarm rate above 2 SDs of the mean were excluded from analysis. Based on this exclusion criterion, three participants were excluded from the analysis (i.e. two participants had a hit rate below 2SDs of the mean and 1 participant had a false alarm rate above 2SDs of the mean).

Out of the four different models explored in the analysis, Model 2 was found to best capture the data regarding response time measure (Table 1). This model included prevalence as a fixed effect and a random intercept for participants and identity. Regarding accuracy measure, Model 3 was found to best capture the data (Table 1). This model included random intercepts for participants and identity as well as prevalence as fixed effect and as a random slope for participants. Results the winning model are reported for each variable respectively.

Response time analysis. Figure 24 (Panel A) shows response time for participants in trials where they gave a correct hit or correct rejection. As prevalence increased, participants were significantly quicker at correctly detecting the target. Analysis indicated a main effect of prevalence on participants' response time, whereby the slowest response time was observed in the low prevalence condition (M = 0.77; SD = 0.26, b = 1.55, SE = 0.04, t = 36.89, p < .001), an intermediate response time was observed in medium prevalence condition (M = 0.71, SD = 0.23, b = 0.09, SE = 0.02, t = 3.78, p <.001) and the fastest response time was observed in the high prevalence condition (M = 0.63, SD = 0.20, b = 0.19, SE = 0.01, t = 13.18, p < .001). This evidence suggests that as prevalence levels increased, response time decreased (Figure 24, Panel A) similar to the effect of prevalence observed in Experiments 4 and 6.

Accuracy analysis. Figure 24 (Panel B) shows participants proportion of errors across all trial types. As prevalence increases, participants' accuracy in target detection increased as their miss rate in target-present trials decreases, indicating a main effect of target prevalence on accuracy, whereby the lowest accuracy was observed in the low prevalence condition (*log odds*= -1.18, SE = 0.23, z = -5.18, p < .001), an intermediate accuracy was observed in the medium prevalence condition (*log odds*= -0.71, SE = 0.27, z =-2.61, p = .009) and the highest accuracy was observed in the high prevalence condition (*log odds* = -1.29, SE = 0.17, z = -7.69, p < .001). This means that the average proportion of miss errors across participants in target-present trials, decreased as prevalence increased (Figure 24, Panel B).

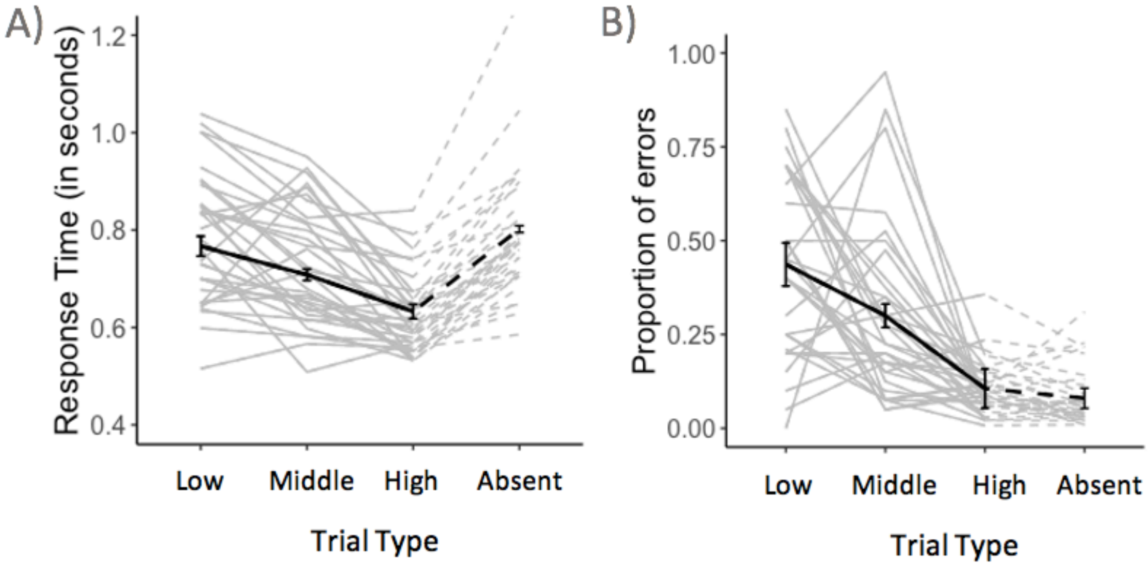
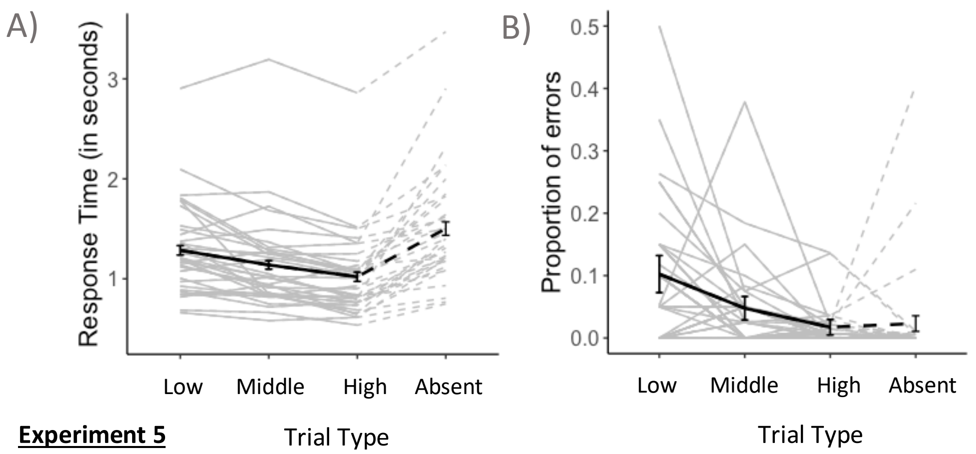


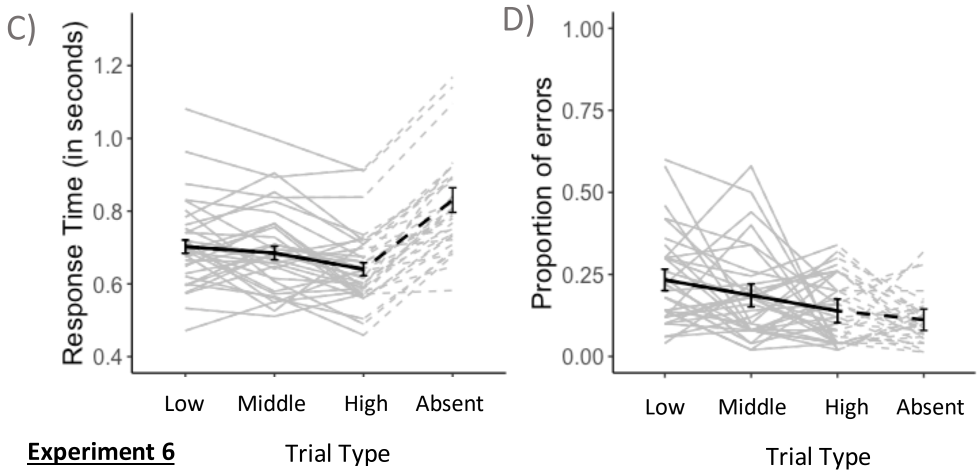
Figure 24. Panel A: Mean Response Time (in seconds) for all participants in target-present (i.e. low, middle and high prevalence) and target-absent trials, in Experiment 7. Panel B: Proportion of errors, for all participants in Experiment 7. In target-present trials (i.e. low, middle and high prevalence), these refer to miss errors whereas in target-absent trials these refer to false alarms. In both panels, black lines indicate mean measures across all participants while grey lines indicate individual data for each participant. Error bars indicate 95% within-subject confidence intervals based on Morey (2008).

Figure 25 presents data from all four Experiments. Looking at the main findings of the Experiments 6 and 7, faster response times and fewer errors are observed in the low prevalence condition of Experiment 6 (Figures 25, Panel E and Panel F, respectively) than in the low prevalence condition of Experiment 7 (Figures 25, Panel G and Panel H, respectively), suggesting that equal (Experiment 7) and unequal (Experiment 6) reward had a different impact on the influence of prevalence on visual search. As a result of this observation, some further exploratory analysis was conducted.

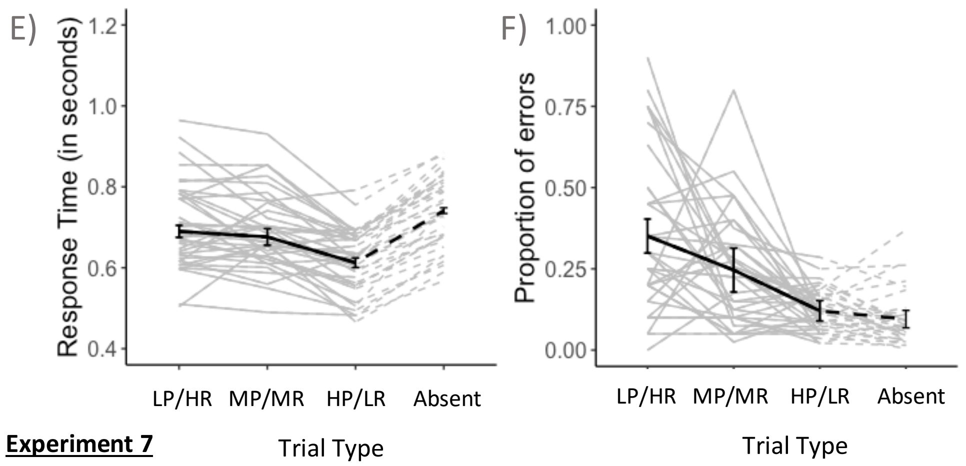
Experiment 4



Experiment 5



Experiment 6



Experiment 7

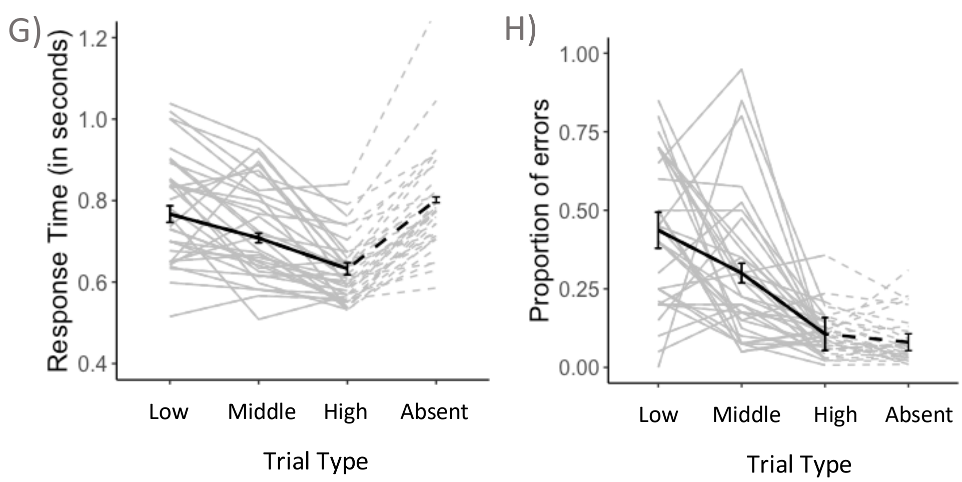


Figure 25. Lefthand Panels (i.e. A, C, E, G): Mean Response Time (in seconds) for all participants in target-present (i.e. low, middle and high prevalence and/or reward) and target-absent trials in Experiments 4-7, respectively. Righthand Panels (i.e. B, D, F, H): Proportion of errors, for all participants in Experiments 4-7, respectively. In target-present trials (i.e. low, middle and high prevalence and/or reward) these refer to miss errors whereas in target-absent trials these refer to false alarms. In all panels, black lines indicate mean measures across all participants while grey lines indicate individual data for each participant. Error bars indicate 95% within-subject confidence intervals based on Morey (2008).

Exploratory analysis

Further exploratory analysis was conducted regarding the effect of priority (prevalence in Experiments 4, 6 and 7; reward in Experiment 5) across all four experiments. The primary aim of this exploratory analysis was to compare the extent to which prevalence influences visual search performance across Experiments 6 and 7 in which reward was manipulated in an unequal (i.e. high reward associated with low prevalence targets and low reward associated with high prevalence targets) and equal (i.e. constant reward associated with low, middle and high prevalence targets) manner respectively. [6] Figure 26 illustrates the coefficients (i.e. beta values from LME analysis of response time in Panel A and log odds from multiple logistic regression analysis of proportion of miss errors in Panel B) of high priority

[6] Although this comparison was part of the original aims of this series of experiments, this analysis is referred to as exploratory as it was not pre-registered and specific tests of this analysis were decided after running Experiment 6 and Experiment 7 and looking at the data.

conditions relative to low priority conditions (reference category) using standard treatment contrast coding. These coefficients show the effect of priority on response time and accuracy of participants between the *high* and *low* priority conditions. The smaller beta values of the LME analysis in Experiment 6 compared to Experiment 7, show a smaller effect of prevalence on participants' response time when reward was manipulated unequally (Experiment 6) versus when reward was manipulated equally (Experiment 7). Similarly, the log odds of the multiple regression analysis on participants' accuracy indicate the chance of making an error in each experiment, with smaller values suggesting a smaller probability of making an error. In particular, the smaller log odds of accuracy in Experiment 6 compared to Experiment 7, indicate a smaller effect of prevalence on participants accuracy when reward was manipulated unequally (Experiment 6) versus when reward was manipulated equally (Experiment 7). This highlights that offering a higher reward to low prevalence targets and a lower reward to high prevalence targets, decreased the influence of prevalence on target detection but not to the extent that it would eliminate or reverse the effect of prevalence.

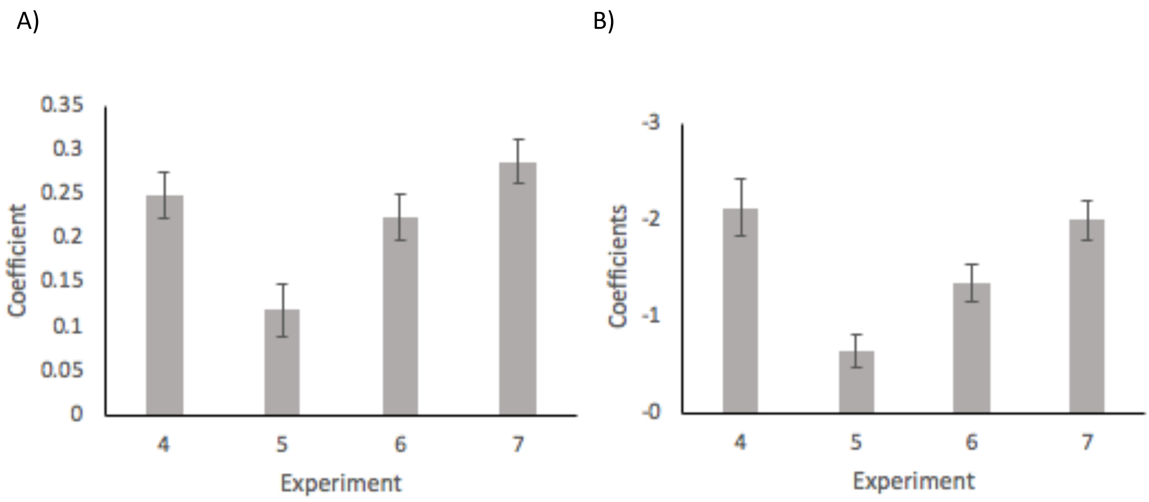


Figure 26. Panel A) Coefficients represent beta values from LME analysis of response time. Panel B) Coefficients represent log odds from multiple logistic regression analysis of proportion of miss errors (i.e. incorrect responses in target-present trials only). In both panels, regression coefficients of the high priority condition relative to the low priority condition (reference category) are plotted. In Experiments 4, 6 and 7 high priority refers to high prevalence condition and in Experiment 5, high priority refers to high reward condition. Error bars represent standard error.

Given the clear difference of the effect of prevalence between Experiment 6 and 7, a further exploratory analysis was performed exclusively on the data from these two experiments. In particular, LME and mixed-effect logistic regression analyses were run for response time and accuracy measures respectively, with ‘experiment’ as a between-subjects factor where Experiment 6 was coded as 0 (reference category) and Experiment 7 was coded as 1. Prevalence was entered as a within-subjects factor with the low prevalence condition as the reference category. In the mixed-effect logistic regression, BOBYQA optimisation was used and correct responses were coded with 0 while incorrect responses were coded with 1.

This analysis aimed to investigate a potential interaction between the within-subject factor of prevalence and the between-subject factor of 'experiment'. Such an interaction would suggest that prevalence influences visual search performance of participants differently across experiments because of the different reward structure. Different models were explored for the analysis of both response time and accuracy and were assessed based on their AIC weights. The structure for each model was the same as the one already specified in the analysis plan section and displayed in Table 1. Model 3 investigated the effects of prevalence and experiment (as a between-subjects factor), as well as the interaction of these two variables, using random intercepts for participant and target identity and prevalence as a random slope for participants. For this exploratory analysis on data from Experiments 6 and 7 with 'Experiment' as a between-subjects factor, model 3 captured the data better than all other models for both response time and accuracy measures. Effect estimates for all levels of both prevalence and experiment variables from the winning model were used for the inferences made below. For both response time and accuracy measures, data was again analysed at the trial level.

Response time measures. The critical interaction between the within-subject factor of prevalence and the between-subject factor of experiment (b = -0.12, SE = 0.05, t = -2.22, p = .03) was significant: the difference between low and high prevalence was more pronounced in Experiment 7 compared to Experiment 6 (b = 0.08, SE = 0.03, t = 2.51, p = .015).

Accuracy measures. Findings suggested an important interaction between the within-subject factor of prevalence and the between-subject factor of experiment (*log odds* = 0.42, SE = 0.28, z = 1.49, p = .134), indicating that accuracy of participants significantly differed across the two experiments between the low and high prevalence conditions (*log odds*= -0.61, *SE* = 0.26, *z* = -2.33, *p* = .019).

The final exploratory analysis, investigated whether repetition effects were driving the benefit for the high prevalence targets. It is well established that participants in visual search tasks can often exhibit repetition effects, whereby participants respond faster and more accurately when a target stimulus is repeated on sequential trials (Hillstrom, 2000; Kristjánsson & Campana, 2009; Maljkovic & Nakayama, 1994). Trials with high prevalence targets are more likely to be repeated than medium or low prevalence trials. Therefore, an LME analysis on participants' response times was performed in Experiment 7, on trials where the high prevalence target appeared after a different trial type (no repetition) or appeared for two, three or four consecutive trials. 'Repetition' was used as a predictor factor with four levels: zero, one, two and three; and the reciprocal response time of participants for correct trials only was entered as a dependent variable. The level of 'zero repetitions' was used as the reference category while sliding differences contrasts were again applied and restricted likelihood and Nelder-Mead optimisation were used. Like the main analysis, different models were again explored and the one with repetition as a fixed effect and a random intercept and random slope for participants was the winning model which was used for the following inferences. Response times were slowest for no repetition trials (M= 0.62, SD= 0.18; b = 1.76, *SE* = 0.04, t = 41.76, p <.001); the first repetition did not result in a benefit (M= 0.61, SD= 0.20; b = 0.02, *SE* = 0.02, t = 0.85, p = 0.41), but the second repetition did (M= 0.60, SD= 0.19; b = 0.09, *SE* = 0.03, t = 2.94, p = .007). There was no further benefit from three repetitions (M= 0.57, SD= 0.15, b = -0.05, *SE* = 0.04, t = -1.32, p = .19). This analysis suggests that participants were quicker at responding to the high prevalence target when it was presented on consecutive trials. However, the no repetition mean response time is still much lower than the low or medium prevalence conditions. Therefore, there is an effect of prevalence over and above the repetition effect.

Overall, the results of the current experiment further support the strong presence of the prevalence effect as participants' response times and accuracy were found to improve as target prevalence increased, irrespective of the reward assigned to targets. An exploratory analysis testing the effect of repeated presentation of high prevalence targets on participants' performance, suggested that prevalence exerted an effect over and above the facilitation in response time that occurs from target repetitions. Experiment 7 included a temporal deadline and a reward, which were present in Experiment 6, allowing for a clearer assessment of the effect of unequal reward on prevalence. Overall, response speed and miss rates were similar between Experiment 6 and Experiment 7. The notable decrease in response time and proportion of misses in the low prevalence condition of Experiment 6, compared to the low prevalence condition of Experiment 7, suggests that participants were more vigilant of low prevalence targets when those were associated with a higher reward compared with other targets versus when all targets were associated with the same reward level.

Exploratory analysis allowed for more detailed comparisons between the findings of the two experiments and the influence of unequal (Experiment 6) versus equal (Experiment 7) reward on the prevalence effect. This analysis confirmed that the effect of prevalence on response time and accuracy was stronger in Experiment 7 than in Experiment 6—the change in response time (Figure 26, Panel A) and accuracy (Figure 26, Panel B) between low and high levels of prevalence was more pronounced in Experiment 7. In addition, a follow up analysis focusing just on Experiments 6 and 7, with 'experiment' as a between-subjects factor suggested a reliable interaction between prevalence and experiment. Given that the only difference between the two experiments was the nature of the reward distribution, this diminished effect of prevalence in Experiment 6 can only be attributed to the unequal reward distribution of the targets. However, instead of running Experiment 6 and Experiment 7 separately and then comparing the data to see differences between unequal (Experiment 6) and equal (Experiment 7) reward distribution on prevalence effect, another option and potentially an idea for a future experiment, would be to directly compare these two conditions in a single experiment where participants would randomly be allocated in the two conditions of reward (i.e. equal and unequal). In the current design where the two reward conditions were compared in two different experiments, lack of random allocation to groups can be argued. However, there is no reason to believe that there is a confounding variable that would lead participants in Experiment 6 to behave differently than those in Experiment 7, especially given that a pre-requisite for participation in these experiments on prolific, was that participants did not take part in any previous experiments of this series. Therefore, current analysis is thought to allow for some conclusive and valid inferences to be drawn.

4.7 Discussion

In the current hybrid task with multiple targets there are two broad questions to be answered: First, can participants prioritise search for some targets versus others in an unequal and graded manner based on their assigned priority? Second, can *unequal* reward be used to modulate the prevalence effect? Taken together, findings from the current experiments suggest that participants are able to prioritise search for specific static targets in an unequal and graded manner based on their priority (prevalence in Experiments 4, 6 and 7; reward in Experiment 5). As priority increased participants were quicker and more accurate at correctly detecting a target. In the current set of experiments, top-down, goal-directed instructions were sufficient to guide hybrid search performance such that participants' efficiency of detecting a target increased as target's associated priority increased as well.

Additionally, a much stronger effect of prevalence on search performance was observed compared to reward, as seen from the smallest effect coefficients of priority in Experiment 5 (i.e. reward manipulation) compared to all other experiments (i.e. where prevalence was manipulated as well; Figure 26). This finding further supports previous studies in which prevalence had an overwhelming effect over and above reward (Clark & Gilchrist, 2018; Jiang et al., 2015; Wolfe et al., 2007; Won & Leber, 2016). However, unequal reward (Experiment 6) did not have a completely negligible effect on prevalence as, when compared to an equal reward (Experiment 7), it was found to diminish the prevalence effect, at least to a degree. The finding that prevalence had a weaker effect on visual search in Experiment 6, suggests that an unequal reward structure channelled some attention to low prevalence targets, which received the highest reward. Therefore, in the current hybrid search task, offering higher reward to low prevalence targets and lower reward to high prevalence targets weakened the prevalence effect, although not to the extent of causing its complete elimination or even reversal.

The finding that unequal reward distribution was not enough to overcome the prevalence effect but was only able to diminish it, suggests that in the current hybrid search task participants are more influenced by prevalence than reward information. These findings contradict previous investigations where researchers assigned a reward to targets in both high and low prevalence conditions and managed to counteract the rarity of low prevalence items (Navalpakkam et al., 2009; Navalpakkam et al., 2010). In such tasks, where single-target (i.e. a line bar) search was performed, equal reward was enough to eliminate the prevalence effect. In the current series of experiments, where participants had to search for three different targets, reward might have not exerted a strong enough impact to eliminate the prevalence effect. This is in line with past findings of Menneer et al. (2010) who investigated prevalence effect in single- versus dual-target conditions and found a much stronger effect of prevalence when participants had to search for an increased number of targets.

The capacity for visually searching for multiple targets has been investigated in the literature but evidence is not yet conclusive (Ort & Olivers, 2020). On the one hand, one line of research supports that as the number of targets to be detected increases, efficiency of visual search decreases (Barrett & Zobay, 2014; Grubert et al., 2016; Mestry et al., 2017). On the other hand, it has also been found that the cost of simultaneously looking for multiple targets can be minor, with observers being able to look for up to 100 objects after sufficient memory training (Drew et al., 2017; Drew & Wolfe, 2014; Madrid & Hout, 2019; Ort et al., 2019; Wolfe, 2012a; Wolfe, et al., 2016), indicating that the capacity of searching for multiple targets could be larger than previously suggested. In the current experiment, top-down goal-directed instructions are found to be sufficient to guide visual search performance such that participants' efficiency of detecting a target proportionally increases with the target's associated priority. The finding that not all three targets were identified with a similar level of efficiency indicates a possibility that searching for multiple targets held in memory is limited and more error-prone than searching for a single one. This provides evidence for a relatively finite resource of working memory and attention which, however, is largely malleable and can be flexibly allocated to different targets in an unequal manner depending on the demands of the task (Alvarez & Franconeri, 2007; Bouchacourt & Buschman, 2019). However, running a future experiment with equal prevalence and equal reward, directly comparing visual search performance during searching for multiple targets and searching for a single target would provide stronger evidence for this assumption. It is possible that the more frequent visual presentation of the high versus the low prevalence targets, improves the mental representation of the former versus the latter, thereby facilitating its detection. This suggestion is in line with principles of statistical learning during visual search, suggesting that frequently repeated patterns in our visual environment are extracted more easily than less repeated ones (Jones & Kaschak, 2012; Turk-Browne, 2012). Given the competition between the representation of the different targets in memory during hybrid search, this stronger representation of the high versus the low prevalence target results in the prioritisation of the former versus the latter (irrespective of the higher reward associated with the low prevalence targets).

Additionally, one could argue that the failure of the unequal reward distribution in eliminating or reversing the prevalence effect results from the fact that this reward pattern was not rewarding or motivating enough to dramatically increase participants' vigilance for low prevalence targets and this can be seen as an important consideration of the this series of experiments. Therefore, future studies should explore different reward structures to investigate what level and distribution of reward may be able to reverse the prevalence effect. For instance, Navalpakkam et al. (2009) did not give the same reward to all types of errors as they employed what they refer to as an 'Airport' and 'Gain' feedback scheme that was found to be highly effective. According to this, participants lost more points for missing a target than for generating a false alarm and gained more points for correctly identifying a target than for correctly rejecting it. Given the positive impact that their reward scheme was found to have in reducing the prevalence effect, it is important to investigate it in a future visual search tasks with *multiple* targets as well, to see if this nullifying effect of reward on prevalence will continue to endure in a task with increased memory demands. Alternatively, Wolfe et al. (2018) also employed the method of both positive (receiving points for correctly detecting a target) and negative (losing points failing to detect a target) feedback in a hybrid foraging task, however the total amount of points gained by participants was not turned into money but was instead used to determine when the task would be terminated. This meant that the higher the number of points received, the quicker the task would end. This was found to be an effective feedback pattern incorporating both reward and punishment, capable of eliminating the prevalence effect. However, Wolfe et al. (2018) used a hybrid *foraging* task in which participants had much more time available to search for the different targets (20 seconds on average). Important differences exist between performance limitations and cognitive demands of foraging versus visual search tasks, primarily deriving from variations in the overall search times available for participants (Gilchrist et al., 2001; Gilchrist & Harvey, 2000). It could therefore be the case that when searching for multiple targets under a tight time constraint (i.e. 1,000ms), reward is not enough to reverse a bias for the most frequently presented targets (i.e. high prevalence) which are easier to detect.

Past literature findings have suggested that the visual search behaviour of participants is strongly mediated by expected value (Milstein & Dorris, 2007; Tobler et al., 2005). In particular, Navalpakkam et al. (2010) compared the impact of reward and prevalence during multiple-target search in a complex perceptual environment. Results indicated that participants' visual search performance was equally guided by both value and salience consistent with a perfect (Bayesian) combination of both priority cues. If this was to be the case in the current visual search task of this thesis, then we would expect complete elimination of the prevalence effect in Experiment 6, given that the expected value across both high prevalence/low reward and low prevalence/high reward conditions was purposely matched (i.e. 0.7 x 1 = 0.7; 0.1 x 7 = 0.7, respectively). However, the stronger effect of prevalence over reward in the current study suggests that participants' behaviour in this hybrid search task is not guided by expected value associated with each target, contradicting past literature findings (Knutson et al., 2005). The current results suggest that different components of the expected value (i.e. probability and value) can be weighted differently in guiding search behaviour.

The aims of the current experiment were to investigate whether participants were able to prioritise search for some targets versus others as well as whether unequal reward can be used to modulate the prevalence effect in a visual hybrid search task with multiple targets. The findings of the current series of experiments suggest that participants are able to prioritise search for some targets versus others in an unequal and graded manner based on their assigned priority (i.e. reward or prevalence). Nevertheless, when the two types of priority were combined, results indicated a stronger effect of prevalence over reward. Two different types of reward distribution were used, equal and unequal, with findings suggesting that neither of the reward schemes was able to eliminate, let alone reverse, the robust effect of prevalence. However, the unequal reward distribution was able to diminish the effect of prevalence on visual search to a certain degree as indicated by faster response times and fewer misses in the low prevalence condition, compared to the equal reward condition. These results further our understanding of how prevalence and reward interact and contribute in our ability to improve visual search performance in critical real-life tasks with important consequences to the health and the security of the public. Current findings could therefore be considered when designing different training sessions used to improve visual search performance of observers in different professions (i.e. airport security screening, medical X-rays; Biggs et al., 2013, 2018; Biggs & Mitroff, 2014; Buser et al., 2020; Meuter & Lacherez, 2016; Mitroff et al., 2018; Nakashima et al., 2013; Spain et al., 2017). Such interventions can incorporate the element of unequal reward to improve vigilance of observers to low prevalence targets. It is worth researching more ways to improve detection of low prevalence targets in real-life visual searches as this can improve outcomes in both medicine and security contexts.

Chapter 5 General Discussion

5.1 Chapter Summary

In Chapter 5, the findings of the current thesis are discussed in relation to theoretical and practical implications unique contributions to the literature, future directions and potential limitations of the current experiments. As stated in Chapter 1, the aim of the current thesis was to investigate unequal attention prioritization of different targets or spatial regions in both dynamic (Chapters 2 and 3) and static (Chapter 4) contexts. This was done through the top-down manipulation of 'priority' which took different forms (i.e. either probability of occurrence/presence or associated reward) and levels (i.e. low, medium and high). Results from both MOT tasks (Chapters 2 and 3) and hybrid search tasks (Chapter 4) of this thesis provide evidence in favour of unequal attention prioritisation of different targets or regions of the visual field, in both dynamic and static contexts. Participants allocated the majority of their attention to high priority targets or regions, yet not completely neglecting the low priority ones. Findings of the current thesis therefore provide some support for flexible accounts of attention indicating that our attentional resource can be flexibly and potentially unequally allocated to different targets or regions in a goal-directed manner depending on task demands. Additionally, findings of Chapters 2 and 3 have important real-life implications regarding the efficiency with which attention can be allocated unequally in different real-life settings like driving and sports playing, as well as the important role of eye movements in this process.. Similarly, findings of Chapter 4 also have critical practical implications regarding the prevalence effect and how this perceptual bias can be eliminated to a certain extent using unequal reward distributions in real-life contexts like airport security screening and medical X-rays. Having established the plausibility to allocate attention unequally in both dynamic and static settings, future experiments should investigate the fine-grained ability of this process and the extent to which evidence for graded prioritisation of targets will still be provided in tasks where more than 3 levels of priority are present.

5.2 Synopsis of Main Findings

5.2.1 Synopsis of Chapter 2

In Chapter 2, unequal attention prioritisation of individual moving targets was investigated during a trajectory MOT task in which two targets were probed with different priorities (i.e. low, equal, high). In this MOT task participants were required to track two targets amongst visually similar distractors while they were all moving around the screen. At the end of the movement all targets disappeared except one and participants had to report the direction to which this target was moving. The two items were identified as targets through the brief presentation of priority labels on them at the beginning of the trial. These numbers represented the probability that participants would be questioned on each of the two items at the end of the trial. Eye movements of participants during tracking were also recorded to investigate exactly how participants divided their attention to the different targets within a trial. Findings indicated that as the priority associated with a target increased, participants' tracking accuracy (for direction of heading judgements) improved in a graded manner while they also looked at or near the high priority target for a larger proportion of time. The findings provide evidence for unequal attention prioritisation of targets as both perceptual performance measures and gaze measures suggested that participants were able to prioritise tracking of high priority targets but did not completely neglect low priority targets.

5.2.2 Synopsis of Chapter 3

In Chapter 3 unequal attention prioritisation of different regions of the visual field is explored in a modified trajectory MOT task where different regions (i.e. top vs bottom, left vs right) were probed with different priorities (i.e. low, equal, high). This MOT task was similar to that used in Chapter 2 with the only difference being that priority numbers were not presented on individual targets but on entire screen regions, indicating the probability that participants would be questioned about any target from that region. Therefore, the screen was divided horizontally in Experiment 2 and vertically in Experiment 3 of Chapter 3. Eye movements of participants were again recorded to investigate how participants allocated their attention to the two screen regions within a trial. Results of Experiment 2 indicated that participants allocated their attention to the different regions in a graded manner, shown by the improved tracking accuracy (for direction of heading judgements) and more frequent and prolonged eye gaze in that region as priority increased. Additionally, as priority of regions increased, tracking precision of participants increased, as well while their proportion of guessing decreased. Experiment 3 aimed to explore the role of eye movements in unequal attention allocation and, therefore, participants performed the task using either overt (i.e. foveal) or covert (i.e. peripheral) vision. Findings indicated that eye movements were functional in that they slightly improved accuracy when participants could freely move their eyes compared to when they had to centrally fixate. Additionally, replicating Experiment 2, better tracking performance was found for high compared to low priority regions, in both the free and fixed viewing conditions, but the benefit was greater for the free viewing condition. Although unequal attention allocation is possible without eye movements, eye movements seem to improve tracking ability, presumably by allowing participants to fixate more in the high priority region and get a better, foveal view of the objects.

5.2.3 Synopsis of Chapter 4

In Chapter 4 unequal attention prioritisation of individual static targets is studied in a hybrid search task where different items were associated with different levels (i.e. low, middle, high) of priority (i.e. prevalence and/or reward). In this task images of unique real-life objects were used and participants had to detect if any of the three targets they held in their memory was present amongst a group of 8 items (i.e. give a target-present or target-absent response). At the beginning of the experiment, participants were presented with the 3 different targets which they had to remember for the duration of the whole experiment, along with their different priority levels. Results indicated that as priority of targets increased, whether this was prevalence (Experiment 4) or reward (Experiment 5), participants' reaction time and accuracy during visual search improved in a graded manner. Additionally, this chapter was concerned with the prevalence effect which refers to the bias of detecting with less efficiency targets which are rarely present (e.g. tumours in X-rays; dangerous items in airport security screenings). Although some studies have attempted to eliminate this effect, most of these studies use *single*-target searches. In Experiments 6 and 7 of Chapter 4, the interaction of prevalence and reward effect was explored, testing whether and to what extent the prevalence effect can be diminished, eliminated or even reversed, through the manipulation of unequal (Experiment 6) or equal (Experiment 7) reward. In Experiment 6 reward was manipulated inversely to prevalence such that as the prevalence associated with a target increased, the reward associated with it decreased. In contrast, in Experiment 7 the same reward was associated with all targets irrespective of their different prevalence levels. Results of Experiments 6 and 7 provided further support for the robustness of the prevalence effect, although unequal rewards (Experiment 6) did diminish the prevalence effect to some extent, compared to equal reward (Experiment 7), as demonstrated by faster reaction times and fewer error rates.

5.3 Theoretical Implications

Overall, the findings of the current thesis provide an insight into how observers allocate their attention unequally to different targets or regions of the visual field, in dynamic and static contexts. Participants were found to allocate their attention in a graded manner to different targets or regions depending on their associated priority with more attention being devoted as priority increases. Evidence indicates the majority of attention was allocated to the high priority target or region yet without completely neglecting the low priority ones, providing evidence for unequal attention allocation.

Regarding the series of MOT experiments of this thesis (Chapters 2 and 3), to the best of my knowledge, they constitute one of the first investigations in the literature on goal-directed *unequal* attention allocation using eye tracking measurements in this paradigm. Apart from inferring attention through perceptual performance (as in Crowe et al., 2019) the experiments reported in Chapters 2 and 3 of this thesis used eye tracking to explore directly how attention is allocated during a trial. Past investigations where attention was only inferred from perceptual performance, could not indicate whether the graded effect of priority on attention was actually a result of allocation attention in a grading manner *within a trial* or a result of mixing trials where the majority, but not all, were trials in which attention was directed exclusively to the high priority target/region. Investigating unequal attention allocation while also monitoring eye movements allows for a distinction to be made between this between-trial mixing and the unequal allocation of attention within a trial. In the current experiments, participants were found to devote their gaze primarily on the high priority target (Chapter 2) or region (Chapter 3) while also monitoring the low priority one to some extent, allowing us to make stronger inferences for unequal division of attention. The current investigations and findings provide some indication for a flexible nature of our attentional structure as it can be allocated unevenly in a demand-based manner depending on the top-down instructions given during the task. This is in line with aspects of flexible theories like the FLEX model (Alvarez & Franconeri, 2007) which posits that attention allocation can dynamically change during tracking such that some targets receive higher amounts of attentional resource than others. The finding from this thesis are therefore incompatible with predictions from fixed architecture theories of tracking, like the Visual Index Theory (Pylyshyn, 1989; 2001; 2007) and Multifocal Theory (Cavanagh & Alvarez, 2005; McMains & Somers, 2004; Müller et al., 2003) that suggest that each target receives a fixed amount of attention (e.g. a visual FINSTs or attentional foci) irrespective of their different associated priorities and as a result would predict similar tracking performance across both targets in a given trial.

It is important to note, however, that for stronger support for the flexible accounts, evidence for fine-grained attention allocation would also need to be provided. The current results simply show that our attention can be divided unequally across three different priority levels yet they do not offer any insight on how fine-grained this ability is and to what extent can our attention be divided in finer increments. Although current results show some flexibility of our attentional structure, for clearer evidence in favour of flexible accounts of attention, future studies could use tasks where the number of targets to be monitored exceed tracking capacity of 4 items and more fine-grained priorities are used (e.g. 20, 30, 50, 70, 80). For example, in a MOT context, such an investigation could include a task where the number of targets is higher than the tracking capacity (e.g. 5 targets) unlike current experiments where either 2 or 3 targets were monitored. It would be interesting to see which targets participants would choose to prioritise (i.e. presumably the targets with the highest priority) and which they would choose to drop completely during tracking (i.e. presumably the targets with the least priority). Also, using more fine-grained priorities would allow us to explore to what extent and to what degree of accuracy, attention can be unequally divided. Is this done solely using a binary mechanism (i.e. high and low priorities) like in the case of the current experiment or would differences be also observed between very low (i.e. 20) versus low priorities (e.g. 30) and between high (i.e. 70) versus very high priorities (e.g. 80)? Such an investigation would shed light on how precisely we can unequally divide our attentional capacity across different targets.

In relation to the series of hybrid search experiments of this thesis (Chapter 4), it is argued that they offer a unique contribution to the literature as they constitute of one of a few visual search tasks experiments where participants had to simultaneously search for more than two targets, something which has largely been overlooked in the literature as the majority of visual search experiments only ever used (mostly) one or (rarely) two targets (Ort & Olivers, 2020). The finding that participants' response time and accuracy improved as priority of targets increased, provided evidence of unequal allocation of attention to different targets based on their associated priorities. The findings of Chapter 4 provide evidence for the flexible nature of our attentional capacity that can be allocated unevenly depending on the demands of the task. This is in line with past findings that indicate that top-down information can guide goal-directed attention allocation and visual search behaviour towards some items versus others in a flexible manner which can dynamically change during the task depending on the different task goals (Awh et al., 2012; Baluch & Itti, 2011).

It is also important to note that recent findings on attention allocation warrant some revision of existing theoretical frameworks on the structure (i.e. fixed vs flexible) of our attentional resource (described in detail in section 2.2.2. of this thesis). Different methodologies are recently employed to investigate attention allocation and these have yielded some important findings that are overlooked by older theoretical frameworks. For example, recent studies looking at eye movements of participants during attention allocation provide important insights into potential strategies observers are employing (Fehd & Seiffert, 2008; 2010) as well as on the role of overt and covert attention (Chapter 3). Therefore, theoretical frameworks based on both eye movement findings and manual response behaviours during attention allocation are thought to offer a more unified understanding of attention allocation and visual search (Hulleman & Olivers, 2017).

Similarly, recent perspectives on visual attention are not considered by older theoretical frameworks (e.g. Cavanagh & Alvarez, 2005; McMains & Somers, 2004; Müller et al., 2003; Pylyshyn, 1989, 2007; 2001). For instance, according to Rensink (2009; 2013) visual attention is viewed as a collection of sub-processes each with its own functions and roles (Rensink, 2009; 2013). For example, according to Rensink (2015) the sub-process of *binding* is the attentional process primarily involved in recognition of different objects during visual search; the sub-process of *holding* is the one which permits the preservation of object representations over time and aids tracking of moving items; while the sub-process of *individuating* is responsible for perceiving unique information like identities of visual targets. It is challenging to investigate the different sub-process of visual attention and their different functions using a single paradigm. For example, according to the arguments of Rensink (2015) in the current series of MOT experiments, it could be argued that the attention sub-process of *holding* was primarily used as participants had to keep track of moving items over a period of time. Alternatively, in the current series of hybrid search experiments the attention sub-process of *binding* and *individuating* might have been more important as participants were visually searching for targets with unique identities. It is important to investigate the process of attention allocation using different paradigms (like in the case of the current thesis where both MOT tasks and hybrid search tasks were used to investigate unequal attention prioritization), in order to investigate different sub-processes of attention which might be involved in different tasks. This allows for a more holistic investigation of visual attention and for more conclusive inferences to be drawn. This recent approach regarding a potential division of visual attention into several sub-processes is largely overlooked by current theoretical frameworks of attention which therefore need to be modified in light of the latest findings of the attention literature. For example, it could be the case that different sub-processes of attention might have different structures and capacities and hence be allocated differently to others.

5.4 Practical Implications

The findings of the current thesis have important practical implications regarding unequal attention allocation in many real-life contexts where targets are either moving (Chapters 2 and 3) or static (Chapter 4). In particular, in contexts like driving, sports playing, medical X-rays or security screenings observers are required to allocate their attention to multiple targets or regions of the visual field which are all important yet to different extents, resulting in unequal attention division. Current findings indicate that whether targets are moving or static, it is indeed possible to allocate your attention unequally between them, primarily focusing on one of these targets or regions (i.e. high priority ones) while also paying attention to others which are of lesser importance yet not completely negligible.

Research findings indicating the plausibility of unequal attention prioritisation can be used to design appropriate cognitive trainings to improve this process in observers who are required to divide their attention to multiple targets simultaneously. For example, 3D MOT training is used to improve attention allocation and decision-making during football playing (Harenberg et al., 2022) or in military settings (Blacker et al., 2019). Interestingly, artificial intelligence algorithms have also been developed that perform MOT in many real-life settings like security footage and CCTV monitoring (Meinhardt et al., 2022; Porzi et al., 2020). In the majority of these contexts though, the MOT tasks used included equal attention splitting. If tasks used for training purposes also incorporated *unequal* attention allocation and considered the role of eye movements in this process as well (e.g. via investigating the tracking strategies used by observers), then they will be able to better reflect real-life conditions and improve performance of trainees in such settings. Given that attention allocation across multiple moving targets is a cognitive ability which can be improved if well trained and practiced (Allen et al., 2004; Green & Bavelier, 2003; Romeas et al., 2016), it is critical to investigate how efficiently attention can be allocated to different moving targets, as well as the contribution of eye movements in this process. In this way we can further understand the structure of our attentional resource and explore pathways of reducing errors in attention demanding tasks in many important real-life tasks.

Additionally, Chapter 4 provides evidence for the possibility to eliminate the prevalence effect to a certain extent using unequal reward distribution where the reward associated with a target increased as its prevalence decreased in order to encourage quick and accurate detection of low prevalence targets. These findings have important implications in real-life sectors like medical X-rays or airport security screenings were efficiency of detecting low prevalence targets (e.g. guns, knives, tumours) is often compromised. For example, this unequal reward distribution used in the current series of experiments could be incorporated in trainings of observers in the aforementioned contexts, where they will be assigned a larger amount of credits or bonus points for detecting low prevalence targets and a lower amount of credits or points for detecting high prevalence targets. In this way observers' sensitivity to low prevalence targets might be increased causing them to respond more quickly and accurately to the targets with the higher importance for the health and safety of the public.

5.5 Limitations and future work

All three empirical chapters of the current thesis provide evidence for the plausibility of unequal attention prioritisation of different targets or regions of the visual field, in both static and moving contexts. However, it is important however to consider potential limitations of the current work and try and address those in possible future experiments. For instance, the ecological validity of the current MOT paradigm used in Chapters 2 and 3 can be challenged as participants had to track identical targets amongst distractors which is unlike real-life settings where observers have to track targets of different identities. It is therefore important to investigate unequal attention prioritisation in different paradigms and tasks where the identity of targets varies and participant have to track realistic items. Such examples include MIT tasks where each moving item has a unique identity (Iordanescu et al., 2011; Oksama & Hyönä, 2016) or the recently introduced Multiple Awareness Paradigms

(MAP; Wu & Wolfe, 2018) where participants are given multiple chances to give a correct response as they are allowed to click on different possible locations until they find the target so that their imprecise knowledge can also be considered. Getting evidence for goal-directed unequal attention prioritisation from tasks with higher ecological validity will offer a better insight into the plausibility and efficacy of this process in real-life settings. For example, it could be the case that unequal attention allocation to multiple moving targets is harder when items have unique identities as there could be larger interference from distractors during movement. In contrast, evidence for the opposite might be provided in such an investigation as tracking targets with unique identity might increase their saliency compared to distractors and therefore make it easier to divide your attention unequally to both of them.

Furthermore, while Chapters 2 and 3 of this thesis investigated the role of eye movements during unequal attention prioritisation of different targets or regions of the visual field, Chapter 4 focused on perceptual performance of participants to infer attention allocation during visual search (i.e. response times and accuracy) as the experiments were performed online and no accurate eye movement measures could be taken at that stage. Therefore, it would be interesting to investigate unequal attention prioritisation of static targets during hybrid search in an experiment where participants' eye movements will also be recorded to explore exactly *how* observers searched for the multiple targets and any potential strategies they might be employing like in the case of MOT. For example, are participants visually searching for the target by visiting each possible item sequentially or do they look at the centre of this collection of items for faster response and try to detect a target with their peripheral vision (Rosenholtz, 2016; Tanrıkul et al., 2020; Watson et al., 2010)? How often do they revisit items during search (Godwin et al., 2015)? Does this depend on memory load during the task (i.e. how many items they have to search for; He & McCarley, 2010;

Solman et al., 2011)? All these are questions which have been investigated in similar visual search experiments where researchers explored eye movements of participants, but little work has been done on answering these questions in cases where attention is divided *unequally* across multiple static items and participants prioritise search for targets of higher importance versus targets of lower importance. Presumably in this case, one would expect more frequent and quicker fixations on a target as its priority increases. Such investigations will shed further light on the nature of our attentional structure and the efficiency with which we can simultaneously attend to multiple targets or regions of the visual field with different importance.

Furthermore, evidence for unequal attention allocation derived from the current thesis provides some support for divided attention however, some future investigations are warranted for clearer inferences to be drawn. Divided attention refers to the ability of observers to simultaneously attend to multiple targets or spatial locations (Shapiro, 2009). While some evidence exists in the current literature for the plausibility of dividing attention across targets (Chong & Treisman, 2005; Emmanouil & Treisman, 2008) and spatial regions (Awk & Pashler, 2000; Alvarez & Cavanagh, 2005), evidence is not yet conclusive, as described in section 1.3 of the current thesis (for more details see Jans et al., 2010). Current findings from all three experimental Chapters of this thesis indicate that participants were indeed able to allocate their attention unequally to different targets (Chapters 2 and 4) or spatial regions (Chapter 3) based on their associated priority, with this effect being observed not only on their averaged performance across trials but on the majority of individual trials as well. Although eye movements recorded in Chapters 2 and 3 indicate unequal allocation of gaze within a trial (i.e. participants allocated more overt attention to a target or spatial region as its priority increased), they do not provide any insight as to whether participants attended these two targets/regions *in parallel* (hence dividing their attention); or they switched their attention between them *serially* (something which would warrant against the plausibility of divided attention) during a trial. A future experiment could try to disentangle between these two possibilities by looking at the number of items which can be processed in a single smooth pursuit during a MOT task with targets of different priority levels. For instance, Hulleman et al. (2020) reported that the number of processed items during a fixation depends on the difficulty of the search task, with multiple items being processed in a task with medium difficulty and only a single item being processed in a task with high difficulty. If both high and low priority targets can be processed (yet to a different degree of accuracy) in a single smooth pursuit then this would warrant evidence in favour of divided attention during unequal attention allocation. It is also important to note that this could depend on factors like speed, inter-object spacing or number of distractors which are all parameters which need to be taken into account in such an investigation.

Regarding the hybrid search task used in Chapter 4, it could be argued that this paradigm is not relevant to real-life settings (e.g. airport security screenings, CCTV monitoring) where observers are searching for a high number of static targets at the same time (Wolfe, 2012). Therefore, it would also be important to investigate the impact of unequal reward distribution on the prevalence effect during a visual search task where more than three targets were simultaneously searched for. Additionally, it is critical to investigate the impact of unequal reward distribution on the prevalence effect during *categorical* search instead of a *target* search. In this case, the whole category of an item would be associated with different levels of prevalence and/or reward and not just individual targets. For example, participants could be searching for any bag, any pair of shoes or any teacup. This would offer a more ecological valid investigation of the prevalence effect in real-life settings as, for example, a TSA agent in the airport security screening is searching for any knife in the knife category and not for a specific knife. Therefore, it would be interesting to see if current findings regarding the elimination of the prevalence effect using unequal reward distribution can also be generalised in a categorical search task.

5.6 Conclusion of thesis

Overall, this thesis aimed to investigate unequal prioritisation of different targets or regions of the visual field in both dynamic (Chapters 2 and 3) and static (Chapter 4) contexts. In a series of MOT tasks, Chapters 2 and 3 provided evidence for unequal attention prioritisation of different targets and regions of the visual field, respectively. In particular, as priority associated with a target or region increased, more attention was allocated to it as indicated by improved tracking performance (for direction of heading judgments). These two chapters also investigated the role of eye movement during unequal attention allocation providing additional evidence for the plausibility of this process as prolonged eye gaze was observed on targets and regions as their associated priority increased. Alternatively, in a series of four hybrid search task experiments (Chapter 4), evidence is provided for a graded prioritisation of different static targets during visual search, based on the priority (i.e. prevalence: Experiment 4; or reward: Experiment 5) associated with each one. This was indicated by quicker and more accurate responses as target priority increased. When the two forms of priority were combined, results indicated that unequal reward distribution (where lower prevalence items are more rewarded; Experiment 6), was found to diminish the effect of prevalence, compared to an equal reward distribution (Experiment 7) as indicated by faster response times and fewer misses. Results of the current thesis provide evidence for a flexible structure of our attentional resource which can be unequally allocated in a goal-directed manner. The findings also provide practical implications for training observers in real-life settings on how to unequally allocate their limited attentional resource in an efficient manner.

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