University of Southampton

Faculty of Environmental and Life Sciences

School of Psychology

Examining the Factors That Influence Selection Choices Within Interactive Search

by

Haden Dewis

ORCID ID 0000-0001-6240-5407

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<u>Abstract</u>

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Historically, human search behaviours have been studied through experimentation using static two-dimensional displays. In these experiments, searchers are tasked with finding target object(s) within visual scenes or amongst stationary distractor objects. However, the vast quantity of theoretical models and research findings fashioned from this approach have one crucial limitation; they overlook the role of physical interactions. The central purpose of this thesis was to address this missing link by conducting search experiments that were interactive in nature. Specifically, these experiments focused upon the factors that drive cognitive decisions regarding which objects or areas to interact with, and how exhaustively to search these before termination. The first set of experiments, presented within Chapter 2, investigated the role of the low prevalence effect within interactive search; a robust effect within visual search by which rare targets are often missed by the searcher. Results revealed standard low prevalence effects upon response accuracy. However, in contrast to visual search, this was not a result of reductions in search exhaustiveness. The second set of experiments, presented within Chapter 3, examined the role of effort on interaction choices. The results confirmed effort to be an extremely strong driver of attentional selection but also highlighted that searchers were often unwilling to terminate a search before having checked and revealed all possible visual information within the display. The final set of experiments, presented In Chapter 4, investigated the important confound of time within interactive search. In the prior experiments, it was unclear whether selection biases were a result of the increased time taken to interact with high effort objects. The findings confirmed that whilst effort was the primary cause, time should not be overlooked within interactive search. Furthermore, results again confirmed that participants were unwilling to leave visual information unchecked within trials. Overall, this thesis and the combined results highlight that the behaviours conducted during visual search are not a good approximation of those conducted during interactive search. Primarily, interactive search tasks are conducted more exhaustively than their visual search counterparts and interaction choices are heavily influenced by the effort and time required to interact with objects.

Table of Contents

Table of Tables

Table of Figures

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I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

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“Make an oath, then make mistakes

Start a streak you're bound to break

When darkness rolls on you

Push on through

Add some years, build some trust

You start to feel your eyes adjust

When darkness rolls on you

Push on through”

Oldies Station, Tyler Joseph

Definitions and Abbreviations

2AFC..............................Two-Alternative Forced Choice

AET ....Attentional Engagement Theory

BF..................................Bayes Factor

BGLMM ....Bayesian Generalised Linear Mixed Effects Models

BLMM.............................Bayesian Linear Mixed Effects Models

CI ....Credible Interval

CT..................................Computed Tomography

FIT ....Feature Integration Theory

FVF ....Functional Visual Field

GPS ....Global Positioning System

GS ....Guided Search

GS2................................Guided Search 2.0

GS6................................Guided Search 6.0

i-MDM ....Interactive Multiple Decision Model

M ....Mean

MDM ....Multiple Decision Model

RTs ....Response Times

SD ....Standard Deviation

SDT................................Signal Detection Theory

SE..................................Standard Error

SERR..............................Search via Recursive Rejection

TAM ....Target Acquisition Model

Chapter 1 Introduction

1.1 General Introduction

Imagine a scenario by which you find yourself stood in front of your open kitchen cupboard in search of a pack of chocolate biscuits to accompany your cup of tea. As you stand there, you visually scan the different shelves of the cupboard hoping to find the elusive chocolate biscuits amongst the various other cupboard essentials. Determining whether the cupboard contained chocolate biscuits is an example of a visual search task. In visual search tasks, the searcher must visually determine whether a target is present amongst various distractor objects (for a review see Wolfe, 2020). It is impossible for a searcher to identify and recognise all visual objects within their field of view at once. As such, visual attention must be directed to relevant areas of the visual scene (Wolfe, 2021). Whilst the consequence of failure to locate a pack of chocolate biscuits is a somewhat less satisfying tea break, there are many real-life examples of visual search where failure to locate the target has severe consequences. Take for example, a radiologist failing to identify cancerous tumours or broken bones on a static X-Ray. As such, over the years, a substantial body of work has been focused on understanding how visual attention is utilised and directed to locate targets, the errors that searchers make, and the associated behaviours and strategies that lead to these (Cain et al., 2013; Eckstein, 2011). Historically, within Psychology, this has been achieved by examining search performance using two-dimensional static displays.

Returning to the previous biscuit example, had you failed to locate the biscuits within the initial visual search, it would have not been considered abnormal to have moved items from the shelves or opened bags and other packets to further examine areas that were previously hidden or obscured. This combination of interaction paired with visual search is referred to as an “interactive search” (Hout et al., 2022; Sauter et al., 2020). One key theoretical difference between visual and interactive search is centred around hidden visual information. In contrast to visual search, during an interactive search, hidden/obscured visual information can be revealed and checked through object interactions. In other words, a searcher can move objects to further check or reveal obscured visual information. What remains unclear is how searchers decide the order in which to interact with specific objects/areas of the current scene and how exhaustively they search those objects/areas. Is it the case that searchers randomly select objects until they stumble upon the target, or are they instead more methodical in their searching? Likewise, how does one decide when to stop interactively searching with specific objects/areas and move to new unexplored ones? Understanding these questions is paramount not only from a theoretical perspective, but from an applied perspective also. Here, an improved understandings of behaviours and strategies is critical for many real-world interactive search tasks where failure to locate the target has severe consequences. For example, airport security hand-searching luggage, police personnel searching prison cells for threats and contraband, search and rescue teams searching for missing individuals, and so forth. Despite this, in comparison to visual search, little is known about interactive search or the factors that guide behaviours and strategies whilst interactively searching for a target. Instead, historically, many visual search findings have simply been applied to interactive search scenarios without consideration to the key differences between the two.

The purpose of the present thesis is therefore to better understand the factors that guide selection processes, behaviours, and strategies during interactive search tasks. The present literature review will begin by detailing previous research on search behaviours and attention within visual search. Following this, the limited research on interactive search will be reviewed before discussing the appropriate next steps and the directions for the remainder of this thesis.

1.2 Visual Search

1.2.1 The Keystones of Early Visual Search

Classic visual search paradigms primarily began around the 1970s (Egeth, 1977; Wolfe, 1998a) and became an extremely popular way to study visual attention during search tasks. In a classic visual search paradigm, static displays are used to present target object(s) amongst several distractor objects on a plain background (see Figure 1.1). By doing so, many of the visual complexities observed within everyday scenes become substantially reduced. Nevertheless, this style of paradigm has allowed for advancements in the understanding of visual attention and enabled the development of numerous models of search. Some of which will now be discussed.

Figure 1.1

Examples of Two-Dimensional Static Displays

Note. Figure depicts three examples of static two-dimensional displays often used within visual search tasks. Within these tasks participants are typically asked to locate targets amongst a set of distractor objects.

An undoubtedly key moment within the history of visual search was the introduction of Neisser's (1967) two-stage pre-attentive architecture of cognitive processing. Here, Neisser suggested that as human beings we perceptually process the environment across two independent cognitive stages. The first of which is a pre-attentive, low-resolution stage, providing basic rudimentary information regarding what is currently being seen, heard, tasted, and so forth. In contrast, the second stage is slow, deliberate, and attentive, allowing for careful inspection of specific stimuli.

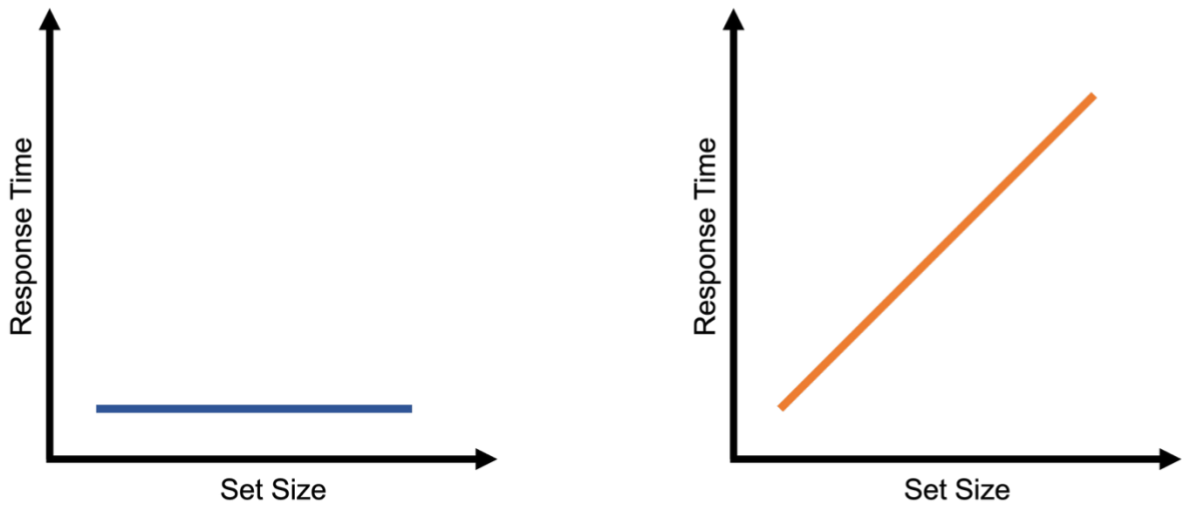
This architecture was applied to several early models of visual search. For example, in Hoffman's (J. E. Hoffman, 1978, 1979) two-stage model of visual search, it was proposed that an initial pre-attentive parallel stage was used to compare all items within a display to the target object. It was believed that this would produce a set of similarity scores between the target and each item within the display, which the second stage would then use to conduct serial inspection in order of decreasing similarity to the target. Hoffman further suggested that the initial parallel stage allowed for immediate identification of targets amongst distractors should they have been dissimilar enough. Likewise, Swensson (1980) suggested a similar two-stage process where an initial pre-attentive parallel stage acted as a filter, selecting subsets of items that contained familiar visual patterns relevant to the target. The second stage was then used to serially inspect these patterns and determine whether they were the target.

A key early theory of visual search comes from Treisman and Gelade (1980) who developed Feature Integration Theory (FIT). Like the previous models, FIT proposed that search consisted of two discrete stages: a pre-attentive parallel stage, and an attentive serial stage. In stage one, the pre-attentive parallel stage, the display was said to have been organised into "attentional maps" which coded the presence and location of all simple features within the display. This stage could be used for what Treisman and Gelade labelled as "feature" or parallel searches. Here, features refer to basic perceptual elements of items such as colour, orientation, size, and so forth. If a target object was sufficiently different to the surrounding distractors based on any one feature, then it would be rapidly detected by the parallel stage without needing to progress to the second stage, i.e., a feature search. The second stage was then utilised when target identification required a conjunction of features to be identified, otherwise known as a "conjunction search" or serial search. Here, it was believed that when objects required a combination of features to be identified, such as colour and orientation, then the visual system would attend to each item serially, in a random fashion, until the target was found or until all objects had been inspected. This focused attention during serial inspections was believed to act as a spotlight and "glue" features together into one perceptual unit.

Although extremely popular, many of the claims made by FIT were later discounted, predominately as a result of inconsistent findings surrounding "search slopes" for feature and conjunction searches. Here, when plotting target acquisition times against the number of distractors within a display (set size), a relationship between the two can be observed in the form of a search slope. As depicted in Figure 1.2, the plotted slope for feature search acquisition times remains consistently flat, regardless of increases in set size. In contrast, for conjunction searches, the acquisition time slope linearly increases with set size. Indeed, under FIT this is logical since the first stage was believed to be limitless and instantaneous whilst the second stage required the searcher to serially inspect each item in the display. As such, increases in set size for a conjunction search, where each item in the display must be inspected one-by-one, should undoubtedly increase response times (RTs). However, research by Quinlan and Humphreys (1987) found that when conducting searches for triple conjunction targets (e.g., target identification requiring three features), it was possible to consistently produce the same flat search slopes that were produced by feature searches. According to FIT, this should not have been possible, as conjunction targets require serial inspection and thus should produce linear search slopes. However, this could be easily explained by the next key model of visual search, known as Guided Search (GS: Wolfe et al., 1989).

Figure 1.2

Search Slopes

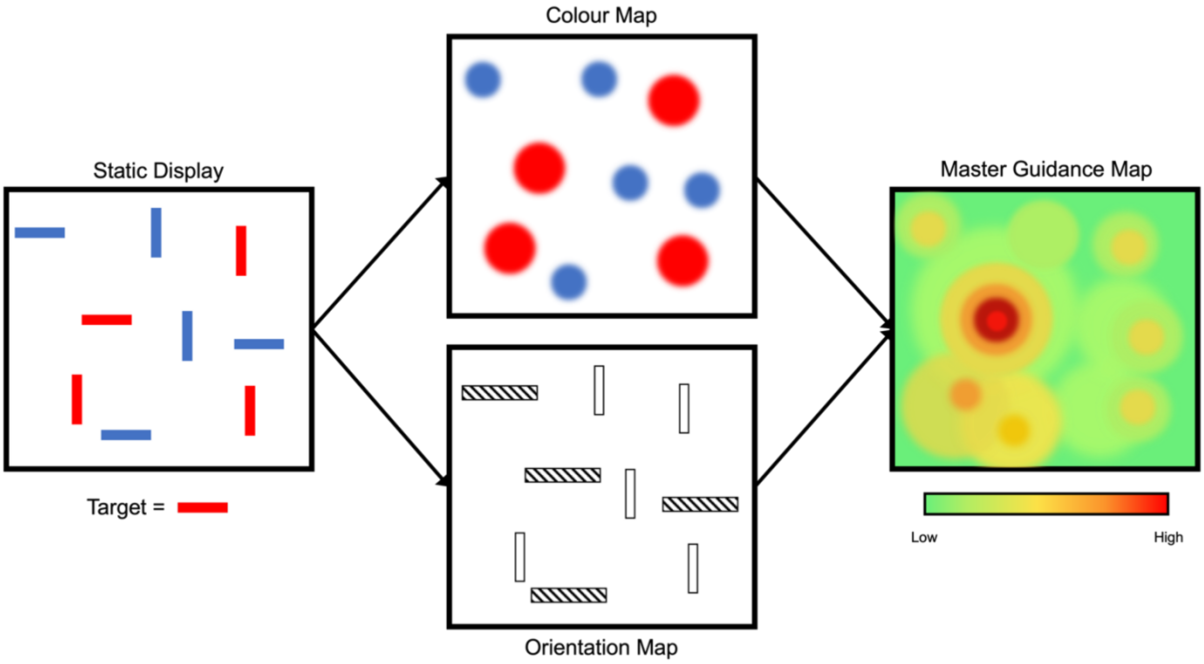


Note. The left panel depicts "parallel", or "efficient" searches, where RTs do not increase with set size. The right panel depicts "serial" or "inefficient" searches, where RTs increase linearly with set size.

Guided Search argued that FIT was too simplistic and needed to be modified to include communication between the parallel and serial stages of search. According to GS, the parallel stage was used to split the visual scene into discrete "pre-attentive maps" which indexed the existence of features within the scene. The outputs of these maps were then summated into a master attentional map which was utilised by the serial stage to automatically guide visual attention to the areas of the display that were most likely to contain the target (see Figure 1.3). Unlike FIT, the GS account could readily explain Quinlan and Humphreys' (1987) findings. According to GS, targets containing multiple features (e.g., triple conjunction targets), should provide stronger featural guidance to the serial stage and thus result in quicker detection, regardless of set size. A revision of GS, known as Guided Search 2.0 (GS2: Wolfe, 1994a) was later released to address several previous shortcomings of GS. The three most prominent of which were changes to the pre-attentive feature map architecture, the inclusion of search termination rules, and the inclusion of activation noise.

Figure 1.3

Guided Search Schematic



Note. Figure depicts a schematic of Guided Search. The visual field is said to be broken down into discrete "pre-attentive maps" which indexed the existence of features within the scene. The outputs of these maps were then said to be summated into a master map used to automatically guide visual attention to the areas of the display that were most likely to contain the target.

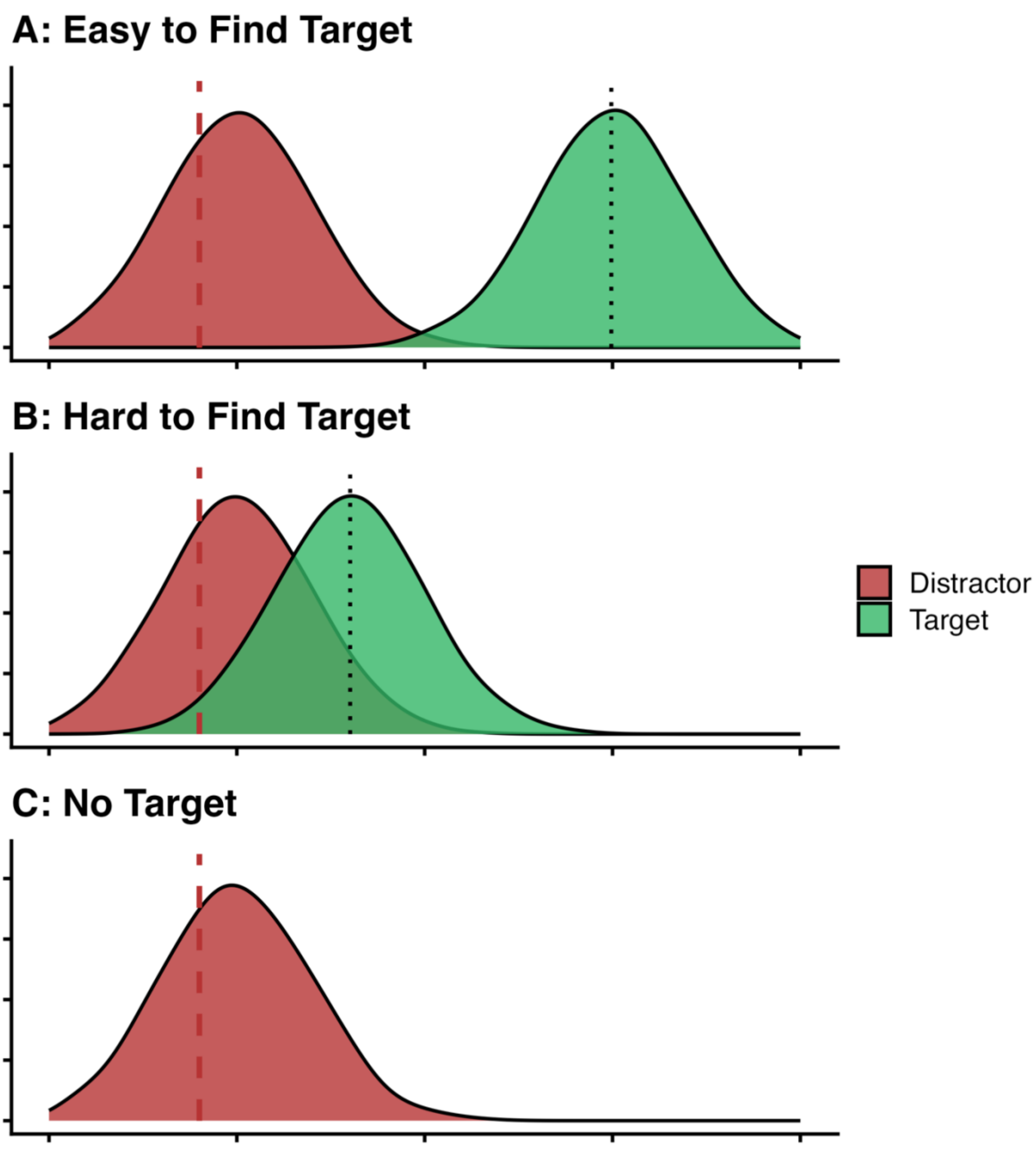
The heart of GS, and consequently GS2, was the notion of pre-attentive feature maps. Whilst GS2 still proposed that a summation of pre-attentive feature maps automatically guided attention, it was further suggested that these maps were more complex than previously thought. As such, GS2 proposed that these maps were derived from a combination of weighted bottom-up and top-down activation. Here, bottom-up activation refers to the physical salience of a stimulus (e.g., a bright object amongst dull objects), and top-down activation refers to the current goals of the searcher (e.g., searching for an object of a specific colour). Based upon prior studies into visual detection of orientation changes (Foster & Ward, 1991a, 1991b; Wolfe et al., 1992; Wolfe & Friedman-Hill, 1992), GS2 specifically postulated that bottom-up activation was not simply a binary operation but was instead a set of filters, broadly tuned to different categorical channels. For example, distinct filters would be used to detect red objects, blue objects, horizontal orientation, vertical orientation and so forth. Objects that were better exemplars of categories (e.g., a perfectly vertical line) would be given greater activation within their associated feature maps. Likewise, top-down activation was modelled as being derived from the outputs of these categorical feature channels. For example, when searching for a red object, areas of the display captured within the red filter would be given greater activation.

Next, GS2 addressed the model's previous inability to explain search termination. Previously, GS had no clear mechanism for how searchers ended a search when a target was not found. This was addressed via the inclusion of activation thresholds driven by a staircase procedure. Simply put, according to GS2, attention should be guided to relevant items within the display based upon the highest activation level produced from the master map. By its very nature this would suggest that at some point, searchers would need to inspect items which had an extremely low level of activation and thus chance of being the target. As such, the concept of an activation threshold was introduced, by which items whose activation levels fell below this cut off were not inspected by the searcher. Based upon prior research into search termination (Chun & Wolfe, 1996), GS2 suggested that this activation threshold was adapted automatically as a result of correct target identification or confirmation of target absence. In other words, if a search ended successfully, the activation threshold would decrease causing subsequent searches to be terminated more rapidly. Likewise, if an error was made, the threshold was assumed to increase, causing subsequent searches to require more searching before termination.

But perhaps the most prominent of all changes within GS2 was the addition of Signal Detection Theory (SDT: D. M. Green & Swets, 1966; Smith & Ratcliff, 2009; Verghese, 2001). GS treated activation levels as fixed values. As such, this would suggest constant perfect guidance to targets, regardless of set size. Clearly this was not the case, and consequently GS2 utilised a SDT framework to introduce noise and variability within activation levels to explain such scenarios. According to GS2, like many tasks in life, visual search could be conceptualised as the detection of target signals against background noise. Here, every item within the display would be assigned an activation value, as determined by the previously stated bottom-up and top-down information, and stored within pre-attentive activation maps. The inputs to these activation maps were said to have come from neurons within the brain, all of which were inherently noisy (Geisler, 1989). As such, repeated exposure to the same item would result in differing levels of activation despite the item remaining consistent. When plotting this activation across numerous search trials for a single target amongst a set of homogenous distractors, two normal distributions occur: one for the distractors and one for the target. The distractor distribution consists of noise primarily from bottom-up activation, whilst the target distribution consists of noise (bottom-up activation) plus a guiding signal (top-down activation). Since top-down activation should provide greater neuron response to target features, the overall distribution for the target should be higher than the distractor distribution. As depicted within Figure 1.4, GS2 claimed that the efficiency of search therefore depended on how strong the guiding signal of the target was compared to the distracting noise. For target-present trials, distractors would be examined if any of their activation levels exceeded the average target activation. This is depicted within panel B of Figure 1.4: distractor items from the left distribution would only be inspected when they exceeded the black dotted line. On target-absent trials however, distractors would only be examined if their activation levels exceeded an observer set threshold, known as the criterion (the dashed line within Figure 1.4). It was believed that this threshold was set so that anything falling below it had an extremely low likelihood of being the target.

Figure 1.4

Signal Detection Theory Schematic



Note. Figure depicts three examples of signal detection theory applied to visual search. The distributions represent neuronal activation for a group of homogenous distractors and a single target. Any item activation above the black dotted line will be inspected and any activation below the red dashed line will be ignored. In panel A, the target is easy to detect; the target can be found without inspecting any distractor items. In panel B, the target is challenging to detect; the activation levels overlap with the distractor activation levels. As such some distractors will likely require inspection before the target is found. In panel C, no target is present, any distractor activation above the observer set criterion will be examined.

1.2.2 Challenges for Early Models

Over the years, advancements in paradigms and experimental procedures have allowed for greater in-depth analysis and understanding of visual attention during search. Particularly prominent within this was the development and increased accessibility of eye-tracking and neuroanatomical techniques. As such, it became clear that visual attention was undoubtedly more complex than earlier models suggested. Many of these early models' assumptions therefore needed to be re-assessed with consideration to these advancements. The challenges to these early models and developments within understandings of visual attention will now be described.

1.2.2.1 Parallel or Serial

The first of many criticisms that these earlier models faced was centred around the construct of parallel and serial stages, such as those suggested by Treisman and Gelade (1980). As opposed to two discrete stages, some suggested that search may be better conceptualised as a continuous scale of search efficiency where serial searches were recast as inefficient and parallel as efficient. This was perhaps best explained through the research conducted by Duncan and Humphreys (1989). In a set of several experiments, Duncan and Humphreys demonstrated that when recast in this way, search efficiency could be based on an interaction between two main factors: the similarity between targets and distractors (T-D similarity), and the similarity between the distractors themselves (D-D similarity). Search was shown to be least efficient when both D-D similarity was low (i.e., the display contained many uniquely different distractors) and T-D similarity was high (i.e., the target looked similar to one of the many different distractors within the display).

Some refuted the idea of a serial stage at all and instead argued that the inefficiency of search was a result of capacity limited parallel processes. Townsend and colleagues were vocal for many years that the methodologies used to assess serial and parallel searches, particularly the use of RTs and set size to compute search slopes, were inadequate and unable to truly differentiate between exhaustive serial inspection and capacity limited parallel processes (Ashby & Townsend, 1980; Townsend, 1990; Townsend & Colonius, 1997; Townsend & Wenger, 2004b, 2004a). Here, instead of serial inspections of individual items, capacity limited processes instead suggests that items within a display were processed in parallel with search efficiency being determined by the number of items the visual system could process in any one chunk. Likewise, Van Der Heijden and Bem (1997) suggested a similar theory and proposed that visual attention was limited by the quantity of information the human eye could capture, with inefficient searches therefore requiring multiple eye movements to process all items within the display.

To further investigate the ongoing debate, (Wolfe, 1998b) conducted an analysis across more than one million different search trials from experimental visual search studies, with the aim of detecting the presence of individual parallel and serial stages. Should there truly be two distinct stages, then a summation of search slopes across these trials should have produced two separate distributions: one for parallel searches and one for serial searches. However, this was not the case. Instead, the resulting distribution from these search trials was a single unimodal distribution. Thus, dispelling the notion of two discrete stages. Instead, this evidence indeed suggested that as proposed by Duncan and Humphreys (1989), from the perspective of search slopes, search was better conceptualised as a continuous scale from low to high efficiency.

For guided search, parallel and serial searches were therefore recast as either efficient or inefficient searches, with the only difference between the two being the amount of useful guidance available to the searcher. Here, useful guidance encompasses a whole host of different facets that may influence search. This includes, amongst others, high quantities of bottom-up salience, e.g., a single bright red colour amongst blue objects (Egeth et al., 1972), or analogously, target-distractor similarity (Duncan & Humphreys, 1989) with higher similarity resulting in a reduction of useful guidance. Where there is clear guidance available, search becomes efficient due to the reduced number of items to search through, and where there is little useful guidance available, search becomes inefficient due to the increased number of items to search through.

1.2.2.2 Eye Movements

Over the last several decades, eye movement research has become a popular method for studying visual cognition as it provides an interesting measure of what is assumed to be overt attention (Godwin et al., 2021; Hutton, 2008; Liversedge et al., 2011; Liversedge & Findlay, 2000). This assumption comes from the fact that eyes predominately move in two distinct ways: saccades and fixations (Liversedge et al., 2011). Saccades are rapid movements that redirect gaze, effectively causing temporary blindness. In contrast, fixations occur when the eyes are held almost stationary for a short period of time (sometimes as short as 50 ms; Rayner, 1998), allowing for the collection of light and thus visual information via the eye. However, the human eye's ability to accurately collect visual information is not perfect. The light sensitive area at the back of the eye, known as the retina, enables the perception of light through the eye. The retina can be split into three main sections: the fovea, the parafovea, and the perifovea. The fovea produces the highest level of visual acuity and is responsible for detailed central vision but covers a mere ~1-2º degrees of visual angle. Next, the parafovea, is a transitional area with lower visual acuity than the fovea. It is utilised for both central and peripheral vision and covers a larger ~5-6º degrees of visual angle. Finally, the perifovea has very low visual acuity indeed and is utilised only for peripheral vision (Balota & Rayner, 1983; Engbert et al., 2002; O'Shea, 1991; Rayner, 1998).

With that said, the high acuity provided by central vision is therefore paramount for accurate detection and interpretation of stimuli. It is perhaps unsurprising then that these central regions of vision have been shown to possess larger processing areas within the brain compared to non-central regions (Carrasco et al., 1995; Daniel & Whitteridge, 1961; Rovamo & Virsu, 1979; Staugaard et al., 2016; Virsu & Rovamo, 1979). Of course, peripheral vision is still utilised within vision, albeit for scenarios where high acuity is not needed, e.g., detecting a bright colour, or a moving object, and so forth (Lleras et al., 2022). Nevertheless, eye movements alone suggest that there is in fact a seriality to vision, moving to new areas when greater detail is required. This was particularly problematic for early models of visual search, many of which rarely referred to eye movements at all. Some researchers argued that when modelling visual search, it should be the overt deployment of eye movements that are modelled instead of covert deployments of attention (Deubel & Schneider, 1996; Zelinsky & Sheinberg, 1995). However, it may not be as trivial as this. Research has also shown that although the number of eye movements increases linearly with set size, they rarely match the total number of distractors within a display (Motter & Belky, 1998a, 1998b; Zelinsky & Sheinberg, 1997). Therefore, multiple objects must be being processed within a single fixation. As such, should models be truly representative of the human experience, then they must include mechanisms for both covert and overt deployments of attention.

1.2.2.3 Re-entrant Networks, Dynamic Filters, and Diffusion Models

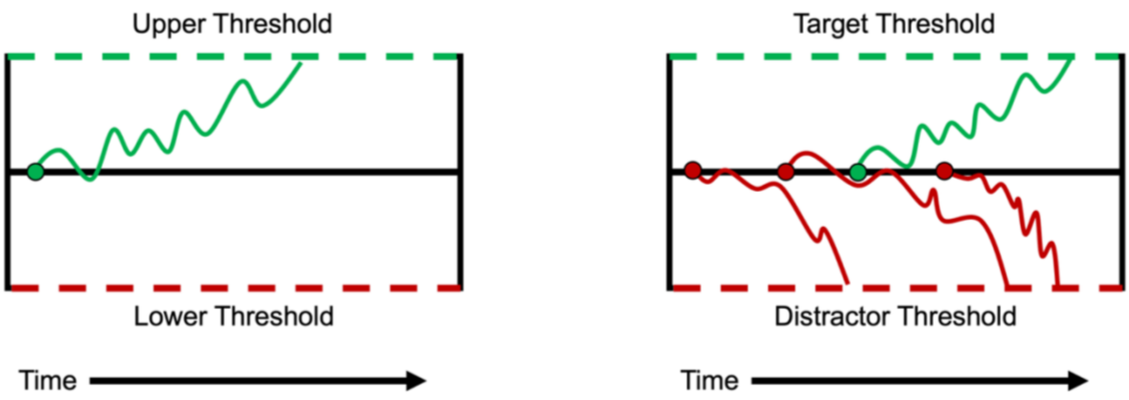
Like eye movements, developments and increased accessibility to neurological methods over the years has allowed for further investigation into the mechanisms involved within visual attention. Many early models of search have taken a linear, or feed-forward approach to describe visual attention and processing (e.g., Itti & Koch, 2001; Koch & Ullman, 1985; Nakayama & Mackeben, 1989; Treisman & Gelade, 1980; Treisman & Gormican, 1988). Under a feed-forward approach, it is suggested that object perception starts with sensory inputs which then propagate to more specialised brain areas where object recognition occurs (e.g., Connor et al., 2004; Yantis, 2005). More colloquially, feed-forward approaches consider visual processing to be a one-way street that begins with simple inputs and ends with complex object recognition. However, neurological research has shown that communication between brain regions are in fact heavily re-entrant in nature (Edelman, 1993; Felleman & Van Essen, 1991; Funahashi et al., 1999). Re-entrant processing describes a feedback process wherein initial streams from low-level brain areas can receive signals from higher-level brain areas, consequently influencing how the brain proceeds to processes information from those initial streams. Within vision, this is believed to be essential for reducing ambiguity and refining perception (Kienker et al., 1986). In other words, re-entrant approaches suggest that visual perception is not a snapshot in time but instead a reconstruction that is built through an iterative process of sensory input and confirmation. Perhaps most vocal regarding re-entrant processing was Di Lollo et al. (2000). According to their re-entrant theory of visual attention, individuals make perceptual hypotheses about objects within the world and then test them against low- and high-level processes. Applied to a visual search example, initial low-level streams send basic features towards the higher-level brain areas within the visual system, a perceptual hypothesis is then made that perhaps the red object in the left of the display is the target object, this is fed back to the lower-level inputs resulting in attention being drawn towards that area. Streams then re-update the higher level brain areas with more information allowing them to determine whether the selected item is the target (Di Lollo et al., 2000, 2001; Lleras et al., 2007; Lleras & Enns, 2005).

As stated previously, many early models of visual attention suggested that numerous discrete feature maps were created within the brain. Di Lollo et al. (2001) took issue with this approach, stating that there was simply not enough physical space within the brain to do so. Furthermore, like many others, Di Lollo et al. (2001) also disputed the idea of discrete parallel and serial stages as a way to explain search times. Instead, Di Lollo and colleagues proposed that visual processing could be better explained by their “Dynamic Filter Theory”. According to the dynamic filter theory, the visual system utilises dynamically configurable input filters controlled by high-level mechanisms within the brain. These filters were said to be configurable to carry out a wide range of tasks including detecting movement, object orientation and so forth. As such, rather than search efficiency being driven by set size (e.g., Treisman & Gelade, 1980), or a lack of guidance (e.g., Wolfe et al., 1989; Wolfe, 1994a), Di Lollo et al. (2001) instead argued that it could be better explained by an inability to rapidly configure these input filters. In visual search terms, it was suggested that inputs were configured to identify targets by filtering out distractors based on their colour, orientation, size, and so forth. If the filters could do this successfully, then search was efficient, if not, then search was inefficient. Wolfe and Horowitz (2004) acknowledged Dynamic Filter Theory but did not agree that these inputs were filters. The term “filter” suggests removal of information, which Wolfe and Horowitz (2004) argued would make many searches impossible. Instead, a more liberal approach was suggested in the form of a high-level control module that guided attention away from non-target information as opposed to a filter that removed it.

Over the years, diffusion models have also become an increasingly popular way to explain visual processing (Ratcliff, 2006; Ratcliff & McKoon, 2008; Ratcliff & Smith, 2004). Not only do diffusion processes resemble many types of parallel search models (Dosher et al., 2004), but they have also been shown to be an effective way to model real RT data for visual search tasks (Ratcliff & Smith, 2004; P. L. Smith & Ratcliff, 2009). The heart of diffusion processes is the collection and aggregation of some type of information. As shown in Figure 1.5, this collection of information begins at a neutral point and progresses towards some threshold as more information and evidence is gathered (Ratcliff & Smith, 2004). Diffusion processes have typically been applied to two-alternative forced choice (2AFC) tasks where people must make one of two decisions. Within vision, 2AFC tasks can occur during higher level object recognition processes (Ratcliff & McKoon, 2008). Here, individuals must determine whether the current object being examined matches any object templates held in long term memory (Carlisle et al., 2011; Grubert & Eimer, 2018; Rajsic et al., 2017). This is not instantaneous; under a diffusion architecture, as information is gradually gathered about an object – e.g., its shape, size, colour, and so forth – it will diffuse towards a threshold that will either confirm or reject whether the current object matches with a template held in long term memory. When applied to a visual search task, as visual information is obtained about an item within the display (e.g., a distractor shape), it will diffuse towards either a target threshold or a distractor threshold. In parallel diffusion models, the accumulation of information is believed to occur for all items at once (Palmer et al., 2000). However, some models instead proposed a more serial approach, suggesting that diffusion only occurs following attentional selection of the item (Wolfe, 2007).

Figure 1.5

Diffusion Model Examples



Note. Figure depicts two separate diffusion processes. The left figure shows a typical diffusion process where information is gradually collected and used to make a two-alternative forced choice. The right figure depicts a diffusion process applied to a search scenario. Here, information is gathered for multiple objects that either diffuse towards a target threshold (e.g., the selected object is the target) or a distractor threshold (e.g., the selected object is a distractor).

1.2.3 Other Poignant Models of Visual Search

There has been many models and accounts of visual search over the years. Although many of these models share similarities between each other, different models emphasise different factors that previous models may have overlooked or chosen to exclude. Consideration and acknowledgment of these models is therefore important in enabling better understanding of visual attention and development of future models of search and attention.

In the late 80s and early 90s there was a handful of researchers interested in the role that object similarity played within visual attention. Most prominent of all was the previously mentioned research by Duncan and Humphreys (1989) on target-distractor and distractor-distractor similarity. This research led to the development of a key early model of visual attention known as Attentional Engagement Theory (AET). AET is a model centred around the idea of structural weighting. Here, structural “units” are provided with a weight relative to how similar they are to the target template (representations of an object held in long term memory) before being passed into visual short-term memory for inspection. Likewise, later work by Humphreys and Muller (1993) aimed to further build upon AET via a new model that they labelled as “Search via recursive rejection” (SERR). SERR proposed that items in the display would clump together to form groups that were dependent upon similarity to the target, similarity to other distractors, and spatial proximity. The visual system could then recursively reject groups through parallel processing where unambiguous grouping had occurred.

Another key set of models come in the form of computational salience models; a result of groundbreaking work from Koch and Ullman (1985) and Itti and Koch (2000a). These models are similar in design to that of GS, however, they are far less focused upon top-down inputs and instead focused largely on the influence of bottom-up inputs and their underlying neurophysiology. Within these models a set of early-vision features are said to create a saliency map that drives both overt and covert deployments of visual attention. These models were less interested in user-driven aspects of search – such as searching for specific targets – and instead aimed to model the salient aspects of the world that could capture visual attention.

Previously, research that suggested that some parts of the visual field could be processed in parallel was discussed (e.g., Treisman & Gelade, 1980). Some groups of researchers have taken this further and argued that visual attention as a whole could be explained solely via parallel processing (Palmer, 1995; Palmer et al., 2000; Verghese, 2001). Within these fully parallel models of search, all items within the visual field are simultaneously handled by a parallel processor that is either limited- or unlimited in capacity. However, when applied to more realistic and complex scenes, issues regarding visual acuity becomes apparent and these models begin to struggle to explain search without considering eye movements.

With that in mind, some models have placed far greater emphasis on the role of overt eye movements in search. One such key model is the Target Acquisition Model (TAM) proposed by Zelinsky (2008). Like GS, the TAM suggested that search was driven by a dynamic activation map modulated by similarity to the target. However, the TAM specifically suggested that this map was used to trigger overt eye movements to specific locations of the display rather than the deployment of covert visual attention.

This focus upon eye movements and the finding that searchers could process multiple objects within a single fixation led to the theory that visual attention operates within what is known as a functional visual field (FVF). There are limits on attentional selection that go beyond simple visual acuity (e.g., Intriligator & Cavanagh, 2001). For example, crowding and masking have been shown to affect object identification of otherwise previously identifiable objects (e.g., Levi, 2008; Levi & Carney, 2009). These combinations of perceptual and attentional constraints produce an FVF: the area of the visual field surrounding a fixation from which an item can still be identified given perceptual constraints (Ball et al., 1988; Engel, 1971; Jacobs, 1986; Sanders, 1970). Rosenholtz et al. (2012) argued that inefficiency of searches was not driven by attentional capacity limits but instead by the limits imposed by crowding and image degradation within these FVFs. This was later conceptualised within Hulleman and Olivers' (2017) model of search known as the FVF model. Within their model it was proposed that search was not conducted in a by-item fashion but instead in a by-FVF clump fashion. Here, searchers are constrained by the number of items that can be processed within each FVF clump. Reduced perceptual and attentional constraints within FVFs would therefore result in more efficient searches.

Most of the aforementioned studies and models throughout this chapter have been based on experiments where the target appeared in 50 % of the search trials. Research has shown that varying the target prevalence (how often a target is present across trials) can affect search performance and behaviour in a substantial manner (e.g., Wolfe et al., 2005, 2007). Put simply, as target prevalence decreases, the speed at which searchers terminate trials increase, and the probability that an observer will identify the target decreases. The Multiple Decision Model (MDM: Wolfe & Van Wert, 2010) is a key model of visual search designed specifically to explain this prevalence effect. The MDM has its roots within GS and SDT. At the most basic level, the model proposes that the visual system must ask two questions at each time point throughout a search. The first is, “is this object the target?” and the second is, “should this search be terminated?”. Should the target be above an observer set criterion, then the selected object will be identified as the target, if not, the item will be deemed as a distractor and a new object will be selected (e.g., GS and SDT). However, throughout this progression, a diffusion process occurs by which an internal signal accumulates towards an adaptive quitting threshold. In other words, as the searcher gains more proof that the target is not present within their current search, they become more likely to terminate the search. The threshold at which this termination occurs is said to be dynamic and driven by the searcher’s beliefs surrounding target prevalence.

Finally, Guided Search 6.0 (GS6: Wolfe, 2021) is now the most up-to-date version of Guided Search. GS6 aimed to account for the issues raised from the previously mentioned literature. The most prominent difference between GS6 and previous models is the belief that the sources of guidance that comprise the attentional priority map are a result of many different factors (e.g., Wolfe & Horowitz, 2017). In previous versions of GS, attention was believed to be guided by only two separate sources of information: top-down and bottom-up feature guidance. In GS6 however, attention is said to be guided by at least five independent sources of pre-attentive information: top-down and bottom-up feature guidance, prior history, reward, and scene syntax and semantics. These sources are said to combine to create a dynamic spatial priority map that is then used to guide attention. Additionally, GS6 considers the role of eccentricity effects and eye movements that were modelled within previous search models (Hulleman & Olivers, 2017; Zelinsky, 2008), and the important role of target templates (e.g., Hout & Goldinger, 2015; Vickery et al., 2005). Here, for an object to be identified as either a target or a distractor, that object’s features must be bound together and compared to the target template held in long term memory. This object recognition stage of GS is modelled as an asynchronous diffusion process, where multiple objects can begin processing at once but objects that exceed the recognition threshold must be accepted or rejected serially. Finally, GS6 continues to model search termination as an accumulating quitting signal with an adaptive threshold.

1.2.4 The Missing Link

Visual search is one of the most researched areas of cognitive psychology (Chan & Hayward, 2013; Eckstein, 2011; Wolfe, 2020b), and consequently, as demonstrated above, we have a truly expansive and rich understanding of it. However, a key drawback of much of this research is its reliance upon static displays within laboratory settings. When considering more real-world examples of search, it is in fact extremely rare for them to be static in nature. Outside of the laboratory, interactive search tasks are the norm not the exception. In other words, most real-world search tasks will involve some kind of interaction, be that rummaging through a bag, foraging through a bush, or simply picking up objects. Likewise, beyond mundane day-to-day search tasks, there are many applied search scenarios that are not only interactive in nature but also have serious consequences when searchers miss targets. For example, search and rescue teams searching through terrain and shrubbery for missing individuals, security personnel searching crime scenes for contraband and evidence, and more besides. Despite this, the research into interactive search pales in comparison to static visual search.

Whilst it is undoubtedly the case that our understanding of visual search can be applied when attempting to understand interactive search behaviours, previous and current research of visual attention overlooks the vital role of interaction within doing so. Gaining a rich understanding of search can therefore not occur whilst research continues to ignore or minimise one of the most prominent aspects of search, the interactions. The following section will detail the limited literature that has attempted to address this missing link and the appropriate next steps.

1.3 Interactive Search

The term interactive search describes searches that involve manipulation of objects within the environment or translation of one’s own physical position with the goal of locating targets or uncovering obscured visual information (Hout et al., 2022; Sauter et al., 2020). These searches can take place across a range of modalities, including on a computer screen (e.g., zooming to find an area on a map), or beyond the computer (e.g., foraging for fruit outside). Interactive searches can range from the mundane (e.g., searching for a snack in a kitchen cupboard) through to the societally important (e.g., forensic searches for evidence). Over the years a number of differing names and methods have been used to describe and assess interactive search. As such, the next section will detail these differences and discuss the limited available literature.

1.3.1 Foraging and Differing Terminologies

Before detailing the current literature, it is important to differentiate between the terms foraging and interactive search. The distinction between the two is somewhat unclear. However, previous literature typically describes foraging as searching interactively for an unknown quantity of a particular target (Barack, 2024). For example, foraging through a bush for berries; the total quantity of berries the bush contains is unknown and termination of this search is not dependent upon the collection of one single target. It is important also note the difference between foraging and dual-target search. In dual-target search, searchers conduct visual searches for two or more targets (e.g., Cain & Mitroff, 2013; Godwin et al., 2010; Stroud et al., 2012). Research on dual-target search has historically focused on the subsequent target misses following initial target detection (Adamo et al., 2019; Cain et al., 2013; Cain & Mitroff, 2013; Fleck et al., 2010). The key difference here is that these tasks are not interactive in nature and therefore do not fall within what is currently considered as foraging. With this in mind, rummaging through a bag for a single set of keys does not neatly fit within the definition of foraging, nor does it fit within the definition of visual search. Despite this, over the years, the term foraging has been used to describe many searches that are interactive in nature yet only require the identification of one target. This has been addressed through the introduction of the term interactive search. Interactive search was first coined by Sauter et al. (2020) and is an umbrella term that encapsulates foraging as well as many other interactive styled searches. As such, unless stated otherwise, within this thesis, the term foraging should be considered as a form of interactive search as opposed to a distinct separate form of search altogether.

With that said, much of the early interactive search work was centred around foraging. There has been substantial work on foraging within animals (see Pyke et al., 1977 for a review) which has gradually been applied to human search tasks. Much of this work has focused on modelling the factors that determine when a forager leaves the current area that they are obtaining resources from, e.g., when they chose to leave their current berry bush and move to a new one. These models (e.g., Marginal Value Theorem: Charnov, 1976) suggest that foragers will optimise their strategies, leaving current areas when the cost of remaining outweighs the costs of moving elsewhere (Andersson, 1978; Ehinger & Wolfe, 2016; Pyke et al., 1977). These models of foraging have since been further applied to static visual search paradigms as a means of explaining deployment of attention (see Bella-Fernández et al., 2022 for a review). Put simply, these models have attempted to explain when a searcher decides to move their eyes to a new area of the display and when they decide to terminate their current search. More recently, research has investigated what has been termed as "hybrid foraging", a type of visual search where observers must search for several targets that may appear an undefined number of times (for an overview, see Wolfe et al., 2016). A real-world example of this might involve cleaning a bedroom where someone must search for objects that need to be put into drawers, or clothes that need washing, and so forth. Research into hybrid foraging has involved participants clicking on objects within static displays using a mouse (Wolfe, 2013; Wolfe et al., 2016, 2019) or touchscreen tablet (Á. Kristjánsson et al., 2014; T. Kristjánsson et al., 2020) to "pick" items. Whilst some work has attempted to recreate real-world search scenarios – e.g., Wolfe (2013) limited the speed at which participants could pick objects to simulate foraging through challenging berry bushes – much of this research has remained focused on static recreations of foraging tasks. In other words, there has been little focus on interactive search within non-static, real-world scenarios.

1.3.2 Initial Steps into Real-World Scenarios

Early work by Gilchrist et al. (2001) attempted to move away from static displays and into the physical realm by examining whether behaviours found in classic visual search experiments still occurred within a more physically dynamic interactive search scenario. In their experiment, searchers had to navigate around a room, interacting with different film canisters that were spread throughout the room, to determine whether they contained a target marble. Results showed that, as is the case for conjunction or inefficient visual searches (e.g., Treisman & Gelade, 1980; Wolfe, 1998b), the time taken to search increased linearly with set size (number of cannisters). However, in contrast to visual search, the frequency at which they rechecked previously inspected objects (e.g., a revisit) was substantially lower than what is typically found within visual search tasks (e.g., Gilchrist & Harvey, 2000). These results therefore suggested that when moving away from static displays, accounts of visual search regarding search exhaustiveness may no longer be able to be straight forwardly applied to interactive scenarios.

A. D. Smith et al. (2008) carried out a similar experiment to further tease apart the differences between visual and interactive search using a series of bespoke lights and switches built into the floor of their laboratory. Within their experiment, participants completed both a visual and interactive search task, specifically with the aim of controlling for the confound of task context, e.g., a visual search on a computer display may not be comparable to visual search within a real setting. Across both conditions, participants were asked to locate a red light amongst an array of green lights. For the visual search condition, all lights were lit on the floor and participants had to locate and walk to the target light, before pressing the attached switch. This was the equivalent of a pop-out or feature search (Treisman & Gelade, 1980). For the foraging condition, participants had to press multiple switches across the floor to see if the light would change from green to red. Results showed that for the visual search task, regardless of the context, behaviours remained consistent with those found in classic feature search studies; set size had no effect on RT and target-absent trials took longer to search than target-present. In contrast, within the interactive condition, RTs increased linearly with set size, but as was the case with Gilchrist et al. (2001), revisits to previous locations were extremely rare. Follow up research again found similar findings (A. D. Smith et al., 2010). Smith and colleagues therefore argued that a comprehensive model of human search behaviours within the real world needed to include aspects of both visual and interactive search.

The previous examples utilised simplistic contexts and did not explore interactive behaviours or strategies in depth. This was likely a result of the complexities and costs involved when assessing interactive search within real contexts. However, over the years several different approaches, both physically and digitally, have been taken to address this and further understand interactive search in less simplistic contexts.

1.3.3 Physical methodologies within Interactive Search

More recently, work by Riggs and colleagues set out to study more applied interactive searches in realistic settings (Riggs et al., 2017, 2018). In their first set of experiments, Riggs et al. (2017) examined the strategies searchers used when searching for targets in open terrain. Participants were tasked with locating a target penny within a grass field whilst their physical position on the field was continuously captured using Global Positioning System (GPS) technology. Alongside standard behavioural measures such as RTs and response accuracy, GPS measurements were used to measure and assess search strategies. Indeed, results revealed that distinct strategies were utilised by participants when searching and that these strategies directly influenced the accuracy of searches. Further research by Riggs et al. (2018) explored interactive search within applied settings such as those typically experienced by police and military personnel. In their experiment, participants were tasked with searching through a fully furnished house for contraband such as guns, money, and drugs. Participants were continuously video recorded throughout their searching and their eye movements tracked via mobile head mounted eye trackers. As before, results revealed differing strategies within participants that varied in effortfulness and were closely tied to the accuracy of searches.

Whilst the previous experiments scored highly in terms of ecological validity, the time and space required to conduct such realistic search tasks, paired with the quantity and complexity of data captured makes it challenging for future research to repeat or expand upon. Research by Sauter et al. (2020) aimed to address this bottleneck through the use of LEGOs®. LEGOs® are small plastic bricks that vary in size, length, and colour and are primarily sold as construction toys. However, their easy accessibility paired with their countless variations in colour and size make them well suited for controlled experimentation. In their research, Sauter et al. (2020), replicated classic visual search paradigms within an interactive format across two experiments by varying set size and target type. In Experiment 1, LEGOs® were piled together in quantities of either 100, 200, or 400 bricks and participants were tasked with finding a single target brick in each. In Experiment 2, set size remained constant and instead target type was varied. Across three conditions, targets were detected via either their colour or their shape, or via a conjunction of features (e.g., size and colour). Results revealed that RTs increased linearly with set size, and that conjunction search was significantly slower than single colour search.

In some separate yet highly related work, Hout et al. (2022), set out to better understand the role of strategy within interactive search across two experiments that also utilised LEGO® as stimuli. Strategy refers to deliberate action planning with the aim of achieving a specific goal. Here, this refers to the processes by which individuals engage in during an interactive search. Perhaps it is the case that individuals will take an “active” approach (e.g., Smilek et al., 2006) and chose to search in a very specific way, e.g., interacting with objects or areas that they deem easy to interact with or areas that contain fewer objects. Or perhaps they may take a more “passive” approach (e.g., Madrid & Hout, 2019), selecting whichever objects pop out to them first. An important facet of interactive search is that interactions facilitate the uncovering of obscured visual information. The strategies used to conduct an exhaustive interactive search therefore have important implications on one’s ability to uncover and detect the target. As such, Hout et al. (2022) followed a similar methodological design to that of Sauter et al. (2020), however they further built upon this by including a hopper to help randomise the placement of LEGO® bricks within trays and by having a researcher log the target identification response times instead of the participant. Results showed that LEGO® bricks were indeed an effective way to assess interactive search and that using an “active” strategy was superior and produced quicker target find times.

1.3.4 Digital methodologies within Interactive Search

Although initial research attempted to move away from the digital realm within interactive search, digital tasks are not innately problematic. The drawback of digital visual search tasks is that displays remain static during searching. In contrast, should objects or areas within the display allow for manipulation or movement from searchers, then this would be considered a valid interactive search task. Indeed, this is a common occurrence within many applied real-world scenarios. For example, this approach is prevalent within next generation airport screening where computed tomography (CT) scanners allow airport screeners to rotate, zoom into, and even slice through scans of passenger luggage (Godwin et al., 2024; Hättenschwiler et al., 2018, 2019; Parker et al., 2022). Likewise, similar CT technologies have long been utilised within the medical field for radiologists who search through scans for abnormalities (Andriole et al., 2011).

Solman et al. (2012) produced some key work within this domain. Across a series of five experiments participants were asked to interactively search through a virtual pile of overlapping objects for a target object. Participants could move objects by clicking and dragging them with a computer mouse. Their methodology was designed to simulate real-world interactive search tasks such as searching through a drawer for an item. Across these five experiments, Solman et al. (2012) varied the difficulty of the task in many ways including manipulations to set size, perceptual load (the quantity of attentional demand the task requires; Lavie et al., 2009), and perceptual difficulty of the stimuli. Solman and colleagues uncovered a novel finding within interactive search that searchers would consistently fail to locate the target despite having directly interacted with it. This finding was consistent across set size manipulations but was influenced by perceptual difficulty and load. As such, Solman et al. (2012) concluded that within interactive searches, two distinct cognitive processes occur: one for planning and initiating physical actions such as arm and hand movements, and one for perceptual identification of stimuli. They argued that dissociations between these two processes were the cause of their observed errors.

As mentioned previously, interactive search is prevalent within many applied settings including radiology within healthcare and next generation airport screening. Whilst the use of CT equipment within airports is new, it has been present for many years within healthcare settings. Despite this, and the heavy focus on radiology within visual search (e.g., van der Gijp et al., 2017), the interactive nature of the search tasks conducted by radiologists has been historically overlooked. Drew et al. (2013) attempted to address this shortcoming within their research. In this work, Drew et al. (2013) utilised a combination of eye movements and interaction measures such as frequency and speed of scrolling, to examine the different strategies used by radiologists when interacting with CT scans for abnormalities. Their findings revealed distinct strategies involving interactions that could not be straight forwardly applied to models of visual search. Drew et al. (2013) acknowledged this and emphasised the need to expand understandings of the behaviours conducted within volumetric search tasks (i.e., interactive search).

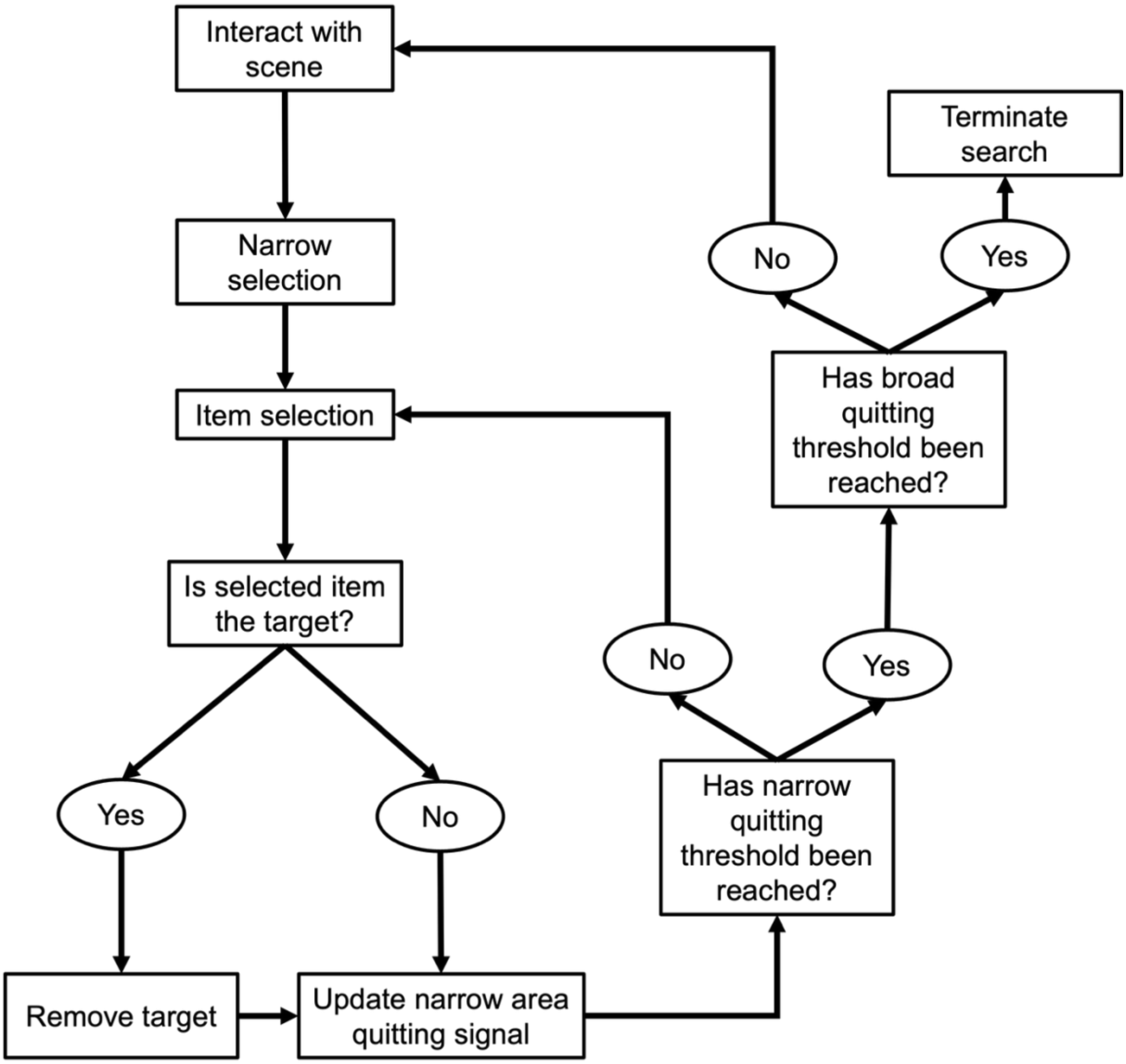
As stated previously, technological advancements have enabled changes within airport screening. As such, many airports have now implemented CT technology when screening passenger luggage for threats. Whilst some research has investigated visual search within these modern CT images (Hättenschwiler et al., 2018, 2019; Parker et al., 2022), to date, Godwin et al. (2024) have been the only team that has allowed searchers to engage in physical interactions and manipulations with these images. Godwin et al. (2024) used a novel methodology that simulated CT scans of passenger luggage which could be rotated and zoomed into using a computer mouse or trackpad. Within this large-scale experiment, search performance was compared between an interactive version of the task and a static version of the task. Findings showed that interactive search resulted in greater accuracy than static visual search at the cost of increased RTs. These results suggest a distinct difference between visual and interactive search in the form of search exhaustiveness. Here, the combination of increased accuracy and RTs suggests that by its very nature, interactive search encourages more exhaustive searching than visual search alone. This again, highlights the importance of the need for improved modelling and understanding of behaviours within interactive search.

1.3.5 The Interactive Multiple Decision Model

In comparison to visual search there is little in terms of models for interactive search. Hout et al. (2022) are currently the only team to have developed a conceptual model designed to explain the steps involved in a typical interactive search. Their model is known as the Interactive Multiple Decision model (i-MDM) and is an expansion of Wolfe and Van Wert's (2010) Multiple Decision Model. According to the i-MDM, the visual field is first broken down into narrow areas that have a high likelihood of containing the target. Following a standard GS approach, the area with the highest density of target-relevant features will be attended to first. Search in the attended area then proceeds as it would in the typical MDM. An item is selected, and a two-alternative force choice is made regarding whether the item is a target or a distractor. If the selected item is not the target, then another decision must be made regarding continuing the search in the specified narrow area. As in the MDM, this is modelled as an accumulating quitting signal. As evidence for the narrow area not containing the target increases, the likelihood of terminating search in that area also increases. If the selected item is instead identified as being the target, then that item is removed, and search continues in the narrow area until the quitting threshold is met. Once this threshold is met, the searcher may then choose to (or choose not to) interact with the scene (e.g., moving the LEGO® bricks with their hands) before selecting the next narrow area to investigate. Throughout this whole process a signal is also said to be accumulating information towards a broad quitting threshold. If this quitting signal crosses the threshold, then the searcher believes that no more targets can be found and that the search needs to be terminated. A figure of the i-MDM is depicted below.

Figure 1.6

The Interactive Multiple Decision Model – Hout et al. (2022)



Note. Hout et al's (2022) Interactive Multiple Decision Model (i-MDM). According to the i-MDM, the visual field is broken down into narrow areas that have a high likelihood of containing the target. The area with the highest density of target-relevant features will be attended to first. An item is selected, and a two-alternative force choice is made regarding whether the item is a target or a distractor. If the selected item is not the target, then another decision must be made regarding continuing the search in the specified narrow area. If the selected item is the target, then the item is removed, and search continues in the narrow area until the quitting threshold is met. Once this threshold is met, the searcher may then choose to (or choose not to) interact with the scene before selecting the next narrow area to investigate.

1.3.6 Next Steps: Guidance within Object Selection

Across all models of search, whether it be GS, parallel diffusion models, FIT, or any of the many others, the most prominent takeaway is that as humans, we cannot meaningfully and simultaneously process all possible pieces of visual information within our field of view at once. As such, should we wish to better understand what it is that we are viewing, our visual attention must be directed towards relevant objects or areas. This is particularly important when considering interactive search tasks. Here, not only are searchers constrained by the limits of their vision but also by their limbs or the extent to which they can translate their body through physical space (e.g., moving forwards or backwards to obtain an unobstructed view). For example, if someone is searching for a screwdriver in a toolbox, should it not be immediately visible, confirmation of the absence of the screwdriver cannot be known until any occluding items have been physically moved. As such, at some point, a cognitive decision must be made to determine which items to inspect or move and how exhaustively these items or areas should be checked. This prompts an important question: what drives these cognitive decisions?

Within visual search it is well established that there are many facets that “guide” our visual attention and influence the strategies we use when searching (Wolfe, 2021; Wolfe & Horowitz, 2017). Over the years, the influence of reward and perceived cognitive effort – otherwise known as value – on search guidance has been extensively studied (Awh et al., 2012; Dayan & Balleine, 2002; Della Libera & Chelazzi, 2006). Value has proven to be a very powerful modulator of guidance. For example, should a searcher be given a monetary reward for every red target they detect, then they become substantially more likely to attend red items first (see Anderson et al., 2011 for an overview). It is important to emphasise that value does not strictly guide attention but instead modulates it. In the prior example, colour is the feature used to guide visual attention, and the learned association of reward simply modulates its effectiveness. Currently, it is assumed that the cognitive decisions regarding which object or area to interact with during interactive search is governed by the same guiding principles as those within visual search. However, there are two fundamental issues with this assumption.

First, within visual search, overt deployment of attention occurs via eye movements (Godwin et al., 2021; Liversedge et al., 2011). In other words, a searcher’s decision to direct their attention towards specific areas or objects is controlled by moving their eyes. Doing so requires very little effort (Araujo et al., 2001). In contrast, a searcher using arm and hand movements to pick up and interact with objects, changing the physical position of their body within a room, or simply using external peripherals such as a mouse or joystick to manipulate imagery all comes at a larger cost both physically and cognitively than simply conducting eye movements alone (Morel et al., 2017; Steelman et al., 2011; Wang et al., 2021; Wickens, 2014, 2015). Although cognitive effort has been shown to influence the strategies used within visual search (Irons & Leber, 2016, 2018), given the low cost of eye movements, its role within search strategy and object selection during interactive search is undoubtedly being underestimated. It therefore seems very likely indeed that searchers would prioritise interactions with objects and areas that reduce required physical and cognitive effort during interactive search.

Second, unlike purely visual search tasks, interactive searches will often follow a three-step process: (1) a visual search of the scene is carried out, (2) if the target is not located, a physical interaction or manipulation is conducted with the search array followed by (or simultaneously) (3) another visual search for the target using the currently available visual information. In other words, vision is used to inform upcoming interactive action and is likely further dynamically determined by an observer's overall goals and search strategies. Put simply, a searcher's overt attention must be directed to the relevant areas or objects they wish to interact with, e.g., selecting a specific wrench within the toolbox. This is fundamentally different from a purely visual search task and as such the little is known regarding how this influences the well-established guiding principles of visual search.

It is, however, important to note that although largely focused on resource collection within animals, much of the previously mentioned foraging literature makes consideration to facets that are believed to mediate decision making. In other words, factors that may guide foraging behaviour. These included peri-personal and extra-personal space (Bertonatti et al., 2021), or more simply put, whether resources within patches are within or out of reach of a forager; The "cost-reward trade off" (Charnov, 1976; Pyke et al., 1977), typically with regard to locomotion, e.g., patches that require greater travel distance come at a greater cost to the forager; Finally, prior expectations (Green, 1980; McNamara et al., 2006), where foragers may inhibit visits to patches that previously did not produce plentiful resources. These are well established factors that have been included within current foraging models e.g., Marginal Value Theorem. Attempts have even been made to apply these models to visual search scenarios (Bella-Fernández et al., 2022). However, a key drawback here is that the foraging literature primarily concerns itself with when to travel to new patches following resource depletion. This is typically at a relatively large scale, e.g., when to leave the current berry bush and head to the next one, or when an animal chooses to leave an environment entirely and travel to a different one. The behaviours that drive object selection within a current patch remain somewhat unclear, e.g., what drives selection of a specific berry on the bush over another berry. It is likely that many of the previously mentioned factors will influence selection choices, however, finer exploration of these is undoubtedly required to confirm this.

With this in mind, whether it be across real, physical, or digital contexts, as has been shown throughout this chapter, what is true of visual search is not inherently true for interactive search. Perhaps most importantly, it is physically impossible to interact with all objects simultaneously within a search. As such, a searcher must meaningfully decide where and what to interact with. Likewise, the requirement of body movements, and the associated physical and cognitive effort involved in doing so at a finer scale is an important and overlooked aspect of interactive search and prior models of foraging. This undoubtedly further influences selection choices and search performance, likely more so than within visual search. Should we wish to truly understand search in all forms, then better understanding of guidance and search strategies within interactive search is paramount.

1.4 Direction for the Current Thesis

This chapter has highlighted that search literature over the years has consistently overlooked the key aspect of interaction within search tasks. This is problematic from both an applied and theoretical perspective. From an applied perspective, many applied search tasks are both interactive in nature and have high consequences when targets are missed. Literature has historically generalised visual search models to these applied search tasks – without consideration to the interactive nature of the task. This is not sufficient and does not allow for successful application of findings to real-world tasks. Likewise, from a theoretical perspective, interactive search is a key component of how search is conducted and therefore it is currently poorly understood. The search literature cannot claim to be able to understand and model real-world search tasks without first understanding the role that interaction plays.

To overcome this, a replicable methodology for studying interactive search was developed and utilised to better understand the factors that guide object selection and the behaviours used during interactions. This was achieved across three independent studies.

In study number 1, the role of target prevalence within interactive search was explored. Many real-life examples of interactive search involve searching for targets that are unlikely to be present or are said to have low target prevalence (Godwin et al., 2024; Riggs et al., 2017, 2018). It is well established within visual search that when prevalence is low, response times (RTs) decrease, response accuracy declines (Wolfe et al., 2005, 2007), and search exhaustiveness reduces (Godwin, Menneer, Cave, et al., 2015; Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015; Rich et al., 2008); this is known as the prevalence effect. Whilst the prevalence effect is well understood within visual search, no past research has examined the prevalence effect within interactive search tasks. To explore this, two interactive search experiments were conducted specifically with the goal of examining search exhaustiveness in interactive search, focusing on whether searchers were less exhaustive when prevalence was low, primarily in terms of behaviour during target-absent trials.

In study number 2, drivers of attentional selection within interactive search were explored. Many different forms of visual input (e.g., colour, size etc.) are known to guide attentional selection within visual search (Wolfe, 2021; Wolfe & Horowitz, 2017). However, little is known regarding attentional selection within interactive search. As such, across two independent experiments, two forms of input that were deemed to be influential within interactive search were explored. The first of these was physical effort (e.g., the physical exertion required to interact with objects), and the second was patch value (the perceived value assigned to different objects or areas containing resources, e.g., Charnov, 1967).

Finally, in study number 3 attentional selection within interactive search was further explored with a specific focus on the role of interaction time. Study number 2 revealed that participants followed an easy-first strategy prioritising interactions with objects that required the least amount of physical effort to interact with. However, high effort objects by their very nature are closely tied with an increase in interaction time. In other words, objects that are hard to interact with typically take a longer time to interact with as well. Perhaps, it was the case that the search system prioritised interactions with objects that could be searched more rapidly, rather than with less effort. As such, to better understand the role of effort and time within interactive search, two independent interactive search experiments were conducted in study 3. These experiments manipulated physical effort but also carefully controlled and manipulated the role of interaction time within these effortful interactive searches.

Chapter 2 No Stone Unturned: Prevalence Effects in Interactive Search are Different to Those in Visual Search

Notes

This chapter is an empirical paper which is currently under review at *Psychonomic Bulletin & Review*.

Authors: Haden Dewis, Cheryl D. Metcalf, Martin B. Warner, Richard Polfreman, & Hayward J. Godwin

CRediT (Contributor Roles Taxonomy)

Dewis: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, validation, writing – original draft preparation. Godwin: Conceptualization, investigation, methodology, project administration, resources, software, supervision, validation, writing – review & editing. Metcalf: writing – review & editing, supervision. Warner: writing – review & editing, supervision. Polfreman: writing – review & editing, supervision.

Open Practice Statement

The raw trial data for both experiments, the final processed datasets, and all associated code used for processing and analysing the data is freely available on the Open Science Framework at https://osf.io/v954y

Abstract

When carrying out a search for a target object, manipulation with the environment may be required to successfully detect the target. These searches are known as *interactive searches*. Many real-life examples of interactive search involve searching for targets that are unlikely to be present or are said to have low target prevalence. To date, the effects of low target prevalence upon interactive search behaviours remain unclear. We conducted two experiments to examine search exhaustiveness in interactive search, focusing on whether searchers were less exhaustive when prevalence was low, primarily in terms of behaviour during target-absent trials. For both experiments, we found a standard effect of low prevalence on response accuracy, such that low prevalence targets were more likely to be missed than high prevalence targets. However, through the utilisation of Bayesian analyses, we found strong evidence against the influence of prevalence upon response times and all other search exhaustiveness measures during target-absent trials. In other words, contrary to visual search findings, changes in response accuracy were not a result of reductions in search exhaustiveness. We conclude that, during interactive search, even when prevalence is low, searchers operate under a ‘no stone unturned’ approach. Under this approach, searchers are unwilling to provide an ‘absent’ response without checking most – if not all – possible places, regions or areas in a display that could contain a target.

Keywords: Interactive Search, Low Prevalence, Visual Search

2.1 Introduction

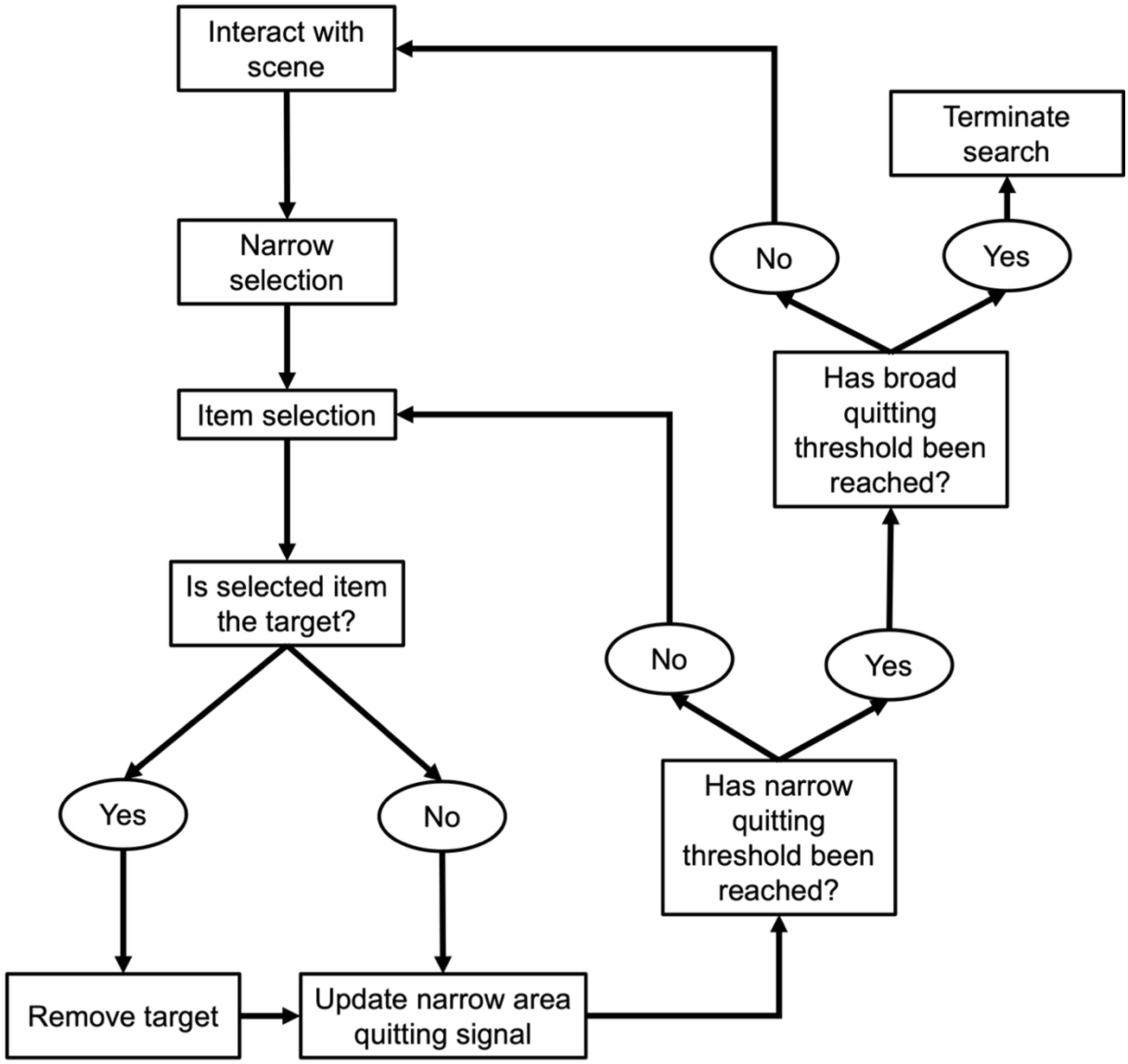
During an interactive search, an observer must physically interact with objects or change their own viewing position to either find a target or confirm its absence (Hout et al., 2022; Sauter et al., 2020). Unlike static laboratory-based visual search tasks, in everyday life, interactive search is the norm rather than the exception. For example, a simple search within our bags for our house keys, the cupboard for a snack, or our desks for a pen. Interactive search is also required for the detection of critical targets in a range of security-scenarios such as airport baggage screening and forensic searches (Godwin et al., 2024; Riggs et al., 2017, 2018). A common issue in these applied search settings is the role of target prevalence. Target prevalence refers to the proportion of searches wherein a target appears (Horowitz, 2017; Wolfe et al., 2007). It is well established within visual search that when prevalence is low, RTs decrease and response accuracy declines (Wolfe et al., 2005, 2007); this is known as the prevalence effect. Here, we examine how the prevalence effect manifests itself within interactive search, with a specific focus on whether shifts in prevalence influence how exhaustive searchers are.

It is important to explore exhaustiveness during low prevalence interactive search because within visual search tasks, when target prevalence is low, exhaustiveness has been shown to reduce. This reduction in exhaustiveness manifests as a decrease in the number of objects examined (Godwin, Menneer, Cave, et al., 2015; Rich et al., 2008) and a reduction in the likelihood of fixating target objects (Godwin, Menneer, Cave, et al., 2015). Likewise, in the rare cases where low prevalence targets are successfully fixated, they are often incorrectly rejected as being distractors (Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015). Whilst the prevalence effect is well understood within visual search, no past research has examined the prevalence effect within interactive search tasks. Studying the prevalence effect in interactive search can therefore help to address a key theoretical issue and difference between visual and interactive search that has not yet been examined to date. During visual search, when a response is made, all available visual information has been presented to the searcher (even if it has not been directly fixated or examined). This is not necessarily the case in an interactive search, as often at least some visual information is obscured until revealed by the searcher. The primary goal of our experiments here was therefore to examine the effects of low prevalence on interactive search. We did this primarily by examining exhaustiveness in low prevalence interactive search. Put another way, we sought to determine whether participants would leave “no stone unturned”, even if they expected each proverbial stone to be unlikely to have a target upon it.

There are some models of animal foraging that have been applied to describe human behaviours within search tasks that are important to consider here (Pyke et al., 1977; Pyke, 2010). In these models, animals (and thus human searchers), are said to be optimal in their foraging; choosing to forage for food in a way that minimises energetic consumption whilst also maximising safety and resource collection. Indeed, under this approach it seems likely that animals would not waste energetic resources foraging for rare objects. However, whilst these models are well suited to describe foraging for food and resources, they are broad, often describing how animals will navigate to new environments or different bushes and trees once resources deplete. Whilst undoubtedly useful, these models align less neatly with more modern real-world search scenarios, e.g., airport staff searching through baggage for rare contraband. To date, the only theoretical model that accounts for interactive search at this much finer human-based scale is that of Hout et al. (2022; see Figure 2.1). Whilst this model does capture search termination, it does not include reference to how comprehensively or exhaustively individuals are willing to search prior to termination. Given the previously mentioned research on prevalence and eye movements (e.g., Godwin, Menneer, Cave, et al., 2015; Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015; Rich et al., 2008; Wolfe et al., 2007), it seems unlikely that searchers will remain exhaustive in their interactive searching when targets are rare. Likewise, as previously mentioned, foraging research suggests that time and energetic resources should be directed towards areas that provide the most benefit to the searcher (e.g., Bremset Hansen et al., 2009; Fryxell, 1991; Van Beest et al., 2010). As such, exhaustively checking for targets that are rarely present is not an optimal approach and seems unlikely (Ehinger & Wolfe, 2016). In addition to simply not checking objects, it has also been shown that searchers reduce the time they spend examining objects when prevalence is low (Peltier & Becker, 2016). In other words, when the target is rare, the speed at which searchers inspect objects increases. As such, it seems probable that in a low prevalence interactive search, searchers will do similar by increasing the speed at which they manipulate and interact with objects as they become more willing to forgo careful inspection. We then have two routes by which targets can easily be missed during interactive search: first, by never revealing them, and second by examining them so briefly that they are missed (e.g., Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015).

Figure 2.1

The Interactive Multiple Decision Model – Hout et al. (2022)

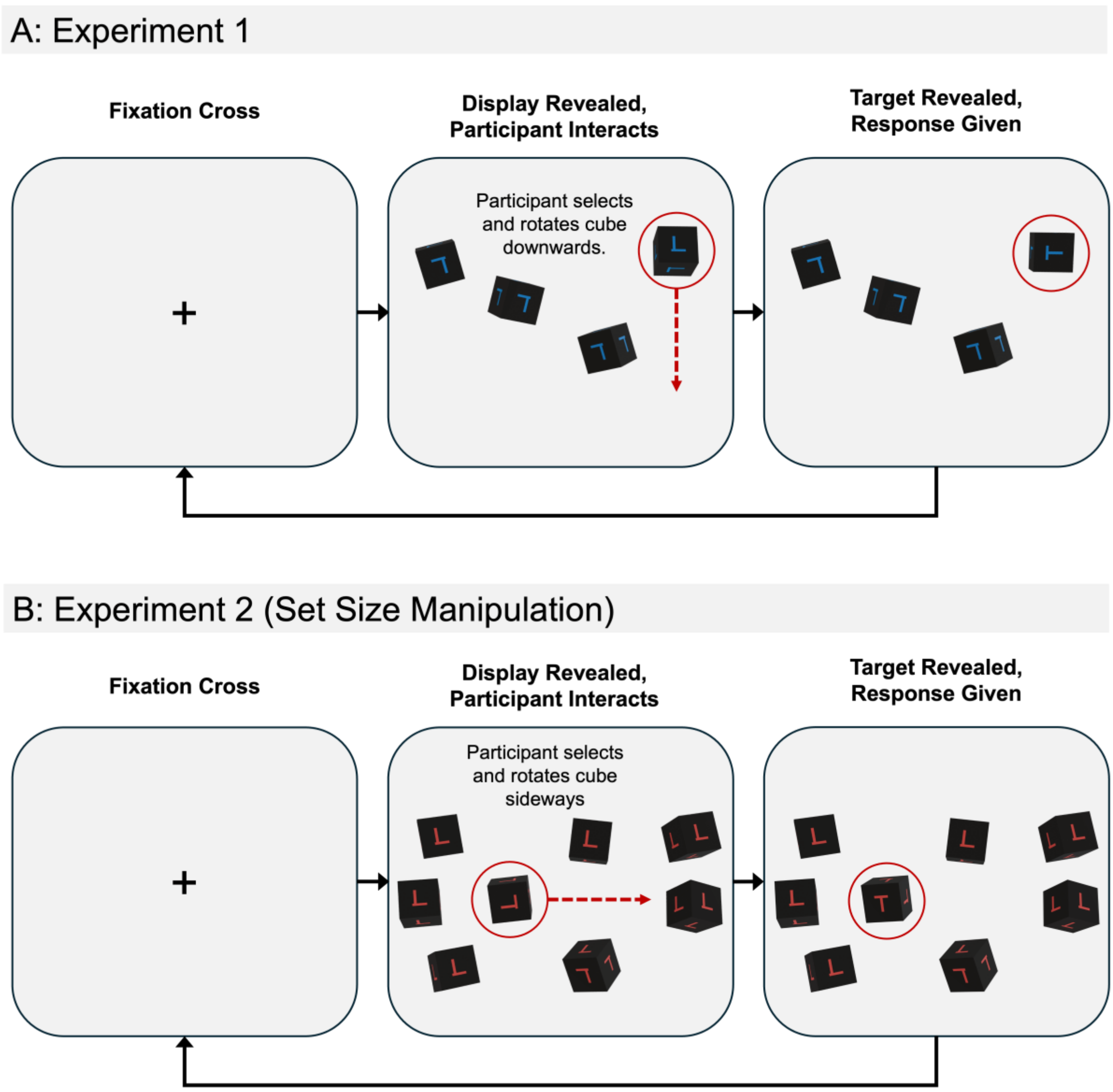


Note. Hout et al's (2022) Interactive Multiple Decision Model (i-MDM). According to the i-MDM, the visual field is broken down into narrow areas that have a high likelihood of containing the target. The area with the highest density of target-relevant features will be attended to first. An item is selected, and a two-alternative force choice is made regarding whether the item is a target or a distractor. If the selected item is not the target, then another decision must be made regarding continuing the search in the specified narrow area. If the selected item is the target, then the item is removed, and search continues in the narrow area until the quitting threshold is met. Once this threshold is met, the searcher may then choose to (or choose not to) interact with the scene before selecting the next narrow area to investigate.

Here, we report the results of two experiments that build upon past work in interactive search (Dewis et al., 2025). We asked participants to search for a T shape placed upon the side of a set of virtual cubes that participants could rotate and examine, see Figure 2.2. In both experiments, we manipulated target prevalence. In Experiment 1, the number of virtual cubes per trial was limited to four, however, in Experiment 2, we increased the set size from four cubes per trial to eight. Our goal within Experiment 2 was to further understand how much visual information participants were willing to leave unchecked when the requirements for an exhaustive search increase, whether this would be further influenced by low prevalence, and again its influence upon the speed of interactions.

Figure 2.2

Trial Procedure for each Experiment



Note. Figure depicts the procedure of a typical trial for both Experiment 1 and Experiment 2. The red circles and arrows were not visible to the participant and are included here to aid visibility. Upon reveal of the display, participants interacted with, and rotated cubes using their cursor, once the target was found (or deemed absent), the participant ended the trial with a keyboard press. This whole process then repeated for 120 trials.

We predicted the following: (1) Response accuracy would decrease when target prevalence was low; (2) Reductions in target-absent RTs would occur when prevalence was low due to early search termination; (3) Participants would become less exhaustive in their searching of target-absent trials as they learnt that the target was rarely present – as evidenced by the proportion of visual information a participant reveals; (4) When target prevalence was low, the speed at which participants checked through cubes would increase as they would not expect objects to contain the target.

2.2 Methods

2.2.1 Ethical Approval

Ethical approval was given by the University of Southampton's Ethics Committee on the 20th of October 2023 (ERGO NUMBER: 89065) for Experiment 1 and on the 11th of July 2024 (ERGO NUMBER: 89065.A5) for Experiment 2.

2.2.2 Transparency and Openness

We report how we determined our sample size, data exclusions, all manipulations, and all measures in the study. Data, materials, and analysis code for all experiments in this study can be accessed online via this web address: https://osf.io/v954y. Experiments were not preregistered.

2.2.3 Participants

A priori power analyses were carried out for both experiments using pilot data from 20 participants, using the *SIMR* package in R (P. Green & MacLeod, 2016). Power analyses were conducted for the first dependent variable being analysed. Target effect sizes were loosely informed by prior research (Godwin et al., 2024) to avoid the issues associated with "observed power" (see Hoenig & Heisey, 2001 for an explanation). Due to the novel nature of this study, we chose a medium standardised effect size. These analyses confirmed that a minimum sample size of 40 participants was required to achieve a power level of 0.80 for Experiment 1 and 50 participants for Experiment 2.

For Experiment 1, 54 participants were recruited from the University of Southampton (Age: *M* = 19.18, *SD* = 1.14, Gender: Female = 82.35 %, Male = 11.76 %, Non-Binary = 2.94 %, Rather Not Say = 2.94 %) during December 2023 and January 2024 and received course credits for their participation.

For Experiment 2, 50 new participants were recruited from the online participant recruitment platform Prolific (Age: *M* = 36.86, *SD* = 12.44, Sex: Female = 44.00 %, Male = 56.00 %) during July 2024. Participants were paid £12.00 for taking part. The Prolific platform allows researchers to set several filters to restrict participation to certain sets of individuals. In Experiment 2, we utilised these tools to apply the following filters when advertising our study: Only include individuals who report themselves as fluent English speakers from the United Kingdom; Only include individuals with a Prolific approval rating of 95% or above. This means that in 95% of the studies they participated in, researchers deemed their data sets as acceptable, with no flaws or failures of attention tests; Only include individuals who have reported having normal or corrected-to-normal vision; Only include participants who report having normal colour vision. Our reason for switching to a Prolific sample for Experiment 2 and applying these filters was to broaden the demographic range from university students whilst also ensuring the highest possible level of data quality.

2.2.4 Stimulus and Apparatus

Stimuli were created using the open-source software Blender (Hess, 2010). Interactive displays were rendered using a Three.js (an open-source JavaScript library that allows three-dimensional graphics to be displayed and interacted with within a web browser) and jsPsych (an opensource JavaScript library used for building web-based psychological experiments) framework (Danchilla, 2012; De Leeuw, 2015).

Stimuli consisted of different cubes with L and T shapes placed onto their faces. Cubes consisted of either a single distractor L shape on each of their six faces, or a single distractor L shape on five of their six faces and a target T shape on the remaining sixth face. The colour of these T and L shapes varied between participants and was selected at random from a set of 16 colours that have been used in previous visual search studies (Godwin et al., 2016; Godwin, Menneer, Riggs, et al., 2015; Stroud et al., 2012). For each trial, cubes were randomly placed into the search array using a 5×3 grid and then randomly rotated through all axes around their point of origin by up to 360º. For Experiment 1, four cubes per trial were used and for Experiment 2, this was increased to eight cubes per trial.

Participants completed the study using their own computers or laptops and associated peripherals. They were told to press the M key of their keyboard if they believed the search array contained a target shape and the Z key of their keyboard if they believed the search array did not contain a target shape. Cubes were interacted with by selecting a cube and dragging their cursor across the screen; the cube would then rotate in the direction of the cursor movement.

2.2.5 Design and Procedure

After consenting to take part, participants were provided with detailed instructions regarding the task followed by a training segment which allowed them to practice rotating a cube for as long as they needed. Participants then went on to complete five practice trials with feedback regarding accuracy, before starting the real trials. All participants then completed a total of 120 trials over the course of ~45 minutes. On each trial, a fixation cross was displayed for 500 ms before the search array was revealed. The search array remained on screen until a response was given. Following a participant response, the search array was removed, the trial ended, and the next trial's fixation cross displayed. A typical target-present trial is depicted in Figure 2.2A for Experiment 1 and Figure 2.2B for Experiment 2.

Participants were randomly allocated to the low prevalence group (target shape present on 10 % of trials) or the high prevalence group (target shape present on 50 % of trials) at the start of the experiment. All remaining trials were target-absent trials.

2.3 Results

2.3.1 Data Cleaning

Prior to all analyses, data underwent pre-planned cleaning. As little is known about interactive search behaviours, and these experiments are exploratory by nature, very little data was removed during this process. We opted to remove data based solely upon RTs across three steps. First, participants with average by-trial RTs longer than 60 seconds (120 seconds for Experiment 2) were removed. During piloting we found that on average, exhaustive search took ~20 seconds (~40 seconds for Experiment 2) per target-absent trial. As such, we chose an average RT cut off that was 3x this value (as is typically done with standard deviation, e.g., Eskenazi, 2023; Godwin et al., 2021; Osborne, 2010). To obtain such a large average RT, participants would have had a substantial number of extremely long search trials. Should this have been the case, this would likely have been a result of the participant not engaging in the task properly and therefore needed to be removed. Second, we removed any trials longer than 180 seconds (360 for Experiment 2). We again chose this value as it is 3x larger than our average cut-off value. Finally, we removed any trials shorter than 250 ms. Within our data analyses, if a stimulus was visible within the display for at least 250 ms then we concluded this visual information to have been visible to the searcher; we have detailed our reasons for doing this within the relevant section below. As such, a small number of trials shorter than 250 ms could not be analysed and were therefore removed. Following all cleaning steps, the final datasets consisted of 6,290 trials from 53 participants (24 from low prevalence, 29 from high prevalence) for Experiment 1 and 5,977 trials from 50 participants (24 from low prevalence, 26 from high prevalence) for Experiment 2. A breakdown of the steps taken and the removed data can be found in Table 2.1.

Table 2.1

Data Cleaning Steps for Each Experiment

	Experiment 1		Experiment 2 (Set Size Increase)	
Removal Step	**Trials Removed**	**Remaining Trials**	**Trials Removed**	**Remaining Trials**
Raw Data	0 (0.00 %)	6,480 (100.00 %)	0 (0.00 %)	5,997 (100.00 %)
Exceeded average cut-off	120 (1.85 %)	6,360 (98.15 %)	0 (0.00 %)	5,997 (100.00 %)
Long Trials	13 (0.20 %)	6,347 (97.95 %)	10 (0.17 %)	5,987 (99.83 %)
Short Trials	57 (0.87 %)	6,290 (97.07 %)	10 (0.17 %)	5,977 (99.67 %)

Note. Exceeded average cut-off = participants' average RTs > 60 seconds for Experiment 1 and > 120 seconds for Experiment 2; Long Trials = Individual RTs > 180 seconds for Experiment 1 and > 360 seconds for Experiment 2; Short Trials = Individual RTs < 250 ms for both experiments.

2.3.2 Analytic Approach

Effects were modelled through Bayesian linear and generalised linear mixed effects models (BLMM, BGLMM) within R (R Core Team, 2023) via the *brms* package (Bürkner, 2017) and findings confirmed using Bayes factors calculated via the *bayestestR* package (Makowski et al., 2019). Bayes factors are the result of a likelihood ratio test between an alternative hypothesis and a null hypothesis. Bayes factors greater than 1.00 indicate stronger evidence towards the alternative hypothesis, whilst Bayes factors of less than 1.00 suggest stronger evidence towards the null hypothesis. For an effect to be deemed trustworthy, it required both a 95% credible interval (CI) that did not pass through zero, and a Bayes factor of greater than 3. We employed a Bernoulli distribution with a logit link for modelling binary measures, a Gaussian distribution with log transformed dependent variables for modelling RT measures, and an inflated Beta distribution for modelling proportional measures. Little is known regarding interactive search and prevalence. As such, due to the novel and exploratory nature of the current study, relatively flat priors were used for all analyses. Models used the same following fixed factors where relevant: Presence (target-absent, target-present), Prevalence (10%, 50%) and Object Order (a continuous measure of order of object interactions). The random effects structure for all models contained random intercepts for participants and random intercepts and slopes for Target Initial Visibility (a measure of whether the target was immediately visible to the participant within a trial). Models that did not use a full random structure did so due to model fitting errors. When models with full random structure returned fitting errors, the random structures were trimmed from the model until model fitting errors no longer occurred.

We analysed standard response accuracy and RT measures in addition to several measures inspired by those found within eye tracking research (see Godwin et al., 2021 for examples). These included the proportion of visual information revealed, and the speed at which participants rotated objects. To compute the proportion of visual information revealed, we measured the number of non-visible cube faces a participant revealed across trials and converted this value into a proportion. A cube face was counted as being “revealed” when it was visible within the display for longer than 250 ms. This value was chosen as it is often used as fixations are typically ~250 ms in duration and thus are often used as a minimum time requirement for registering successful object identification within eye tracking research (Godwin et al., 2021; Liversedge et al., 2011; Rayner & Pollatsek, 2006). Additionally, this value has been successfully used within previous interactive search experiments (Dewis et al., 2025). Whilst we acknowledge that identification can happen at a faster rate (e.g. Kirchner & Thorpe, 2006), we have erred on the side of caution here, potentially underestimating effects, to ensure that we have only counted a face as being revealed if it truly was.

2.3.3 Findings

We report effects from all analyses within Tables 2.2 and 2.3, and visually depicted descriptives in Figure 2.3. We found the standard effects of prevalence upon response accuracy rates. This was evident across both experiments within a Presence x Prevalence interaction (Experiment 1, High Prevalence Present Vs. Low Prevalence Present: *Estimate* = -0.74, *lower CI* = -1.38, *upper CI* = -0.07, BF_{10} = 3.27. Experiment 2, High Prevalence Present Vs. Low Prevalence Present: *Estimate* = -0.89, *lower CI* = -1.55, *upper CI* = -0.22, BF_{10} = 9.65).

Despite this, prevalence had little influence anywhere else. In RTs, we failed to find the standard effects of low prevalence on target-absent trials: in fact, we found strong evidence *against* any changes in RTs for target-absent trials for both experiments ($BF_{10's}$ <= 0.11).

With regards to search exhaustiveness, to our surprise, we again found strong evidence *against* any effects of prevalence ($BF_{10's}$ <= 0.25), participants remained extremely exhaustive within target-absent trials, revealing on average ~95 % of visual information across both experiments.

Likewise, within our analyses of speed, we again found strong evidence *against* any effects of prevalence ($BF_{10's}$ <= 0.27). Despite objects rarely containing the target within the low prevalence condition, the average speed at which participants rotated and manipulated cubes remained consistent between prevalence conditions, averaging at ~4 rad/s for both prevalence conditions over both experiments.

However, across all analyses we found that when comparing target-present trials to target-absent trials, RTs were quicker, the quantity of visual information uncovered was less, and the average speed of rotations was slower. These effects are best explained as a result of early trial termination following target detection. In these cases, the participant would not need to interact with all four cubes thus resulting in quicker RTs, less visual information being revealed, and less variable speed data. More specifically, the reason for this reduction in variability within the speed data comes down to how the speed measure is calculated. Speed is calculated as an average of all cube rotations conducted throughout a trial. If a participant rotates only one cube within a trial before detecting the target, then the speed at which they did this was likely mostly consistent. In contrast, in a trial by which all four cubes were interacted with and the target not found, then it is likely that participants would be more inclined to change the speed at which they interacted with objects: slowing down or speeding up to recheck previously seen faces. Since it is rare that a participant would need to interact with all four cubes before detecting a target, target-present trials therefore produced less variable speed readings.

Table 2.2

Modelled Effects and Bayes Factors for Experiment 1

	Accuracy				RT		
Parameter	*Estimate*	*CI*	*BF_{10}*	*OR*	*Estimate*	*CI*	*BF_{10}*
Intercept	3.36 (0.19)	**3.00 – 3.74**	**7.00×10^{20}**	28.76	9.16 (0.08)	**9.00 – 9.32**	**7.99×10^{129}**
Prevalence (Low, High)	0.00 (0.34)	-0.67 – 0.65	0.33	1.00	-0.12 (0.10)	-0.32 – 0.08	0.21
Presence (Absent, Present)	-3.69 (0.21)	**-4.11 – -3.30**	**7.32×10^{21}**	0.02	-0.58 (0.03)	**-0.65 – -0.52**	**2.50×10^{19}**
Prevalence × Presence	1.46 (0.39)	**0.71 – 2.22**	**218.19**	4.32	-0.06 (0.06)	-0.19 – 0.05	0.11
	Visual Information Revealed				Speed		
Parameter	*Estimate*	*CI*	*BF_{10}*	*OR*	*Estimate*	*CI*	*BF_{10}*
Intercept	0.49 (0.05)	0.40 – 0.58	**2.28×10^{10}**	1.63	3.34 (0.17)	**3.02 – 3.67**	**7.59×10^{19}**
Prevalence (Low, High)	-0.04 (0.08)	-0.21 – 0.12	0.10	0.96	0.15 (0.20)	-0.25 – 0.54	0.26
Presence (Absent, Present)	-1.06 (0.06)	**-1.17 – -0.94**	**6.14×10^{16}**	0.35	-0.24 (0.06)	**-0.35 – -0.13**	**218.84**
Prevalence × Presence	-0.07 (0.12)	-0.30 – 0.16	0.14	0.94	0.08 (0.11)	-0.14 – 0.30	0.14

Note. CIs = Credible Intervals; BF = Bayes Factor; OR = Odds Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. All R-Hat values = 1.00. Effects were deemed reliable if CIs did not pass through zero and BF > 3.00. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite. E.g., participants were less likely to be correct in target-present trials than they were target-absent trials.

indicates that the outcome is more likely to occur as the predictor increases (or relative to the reference group), while an $OR < 1.00$ indicates a decrease in likelihood. For example, the OR of 0.02 for "Presence" indicates a 98% reduction in the odds of the outcome compared to the reference category.

Table 2.3

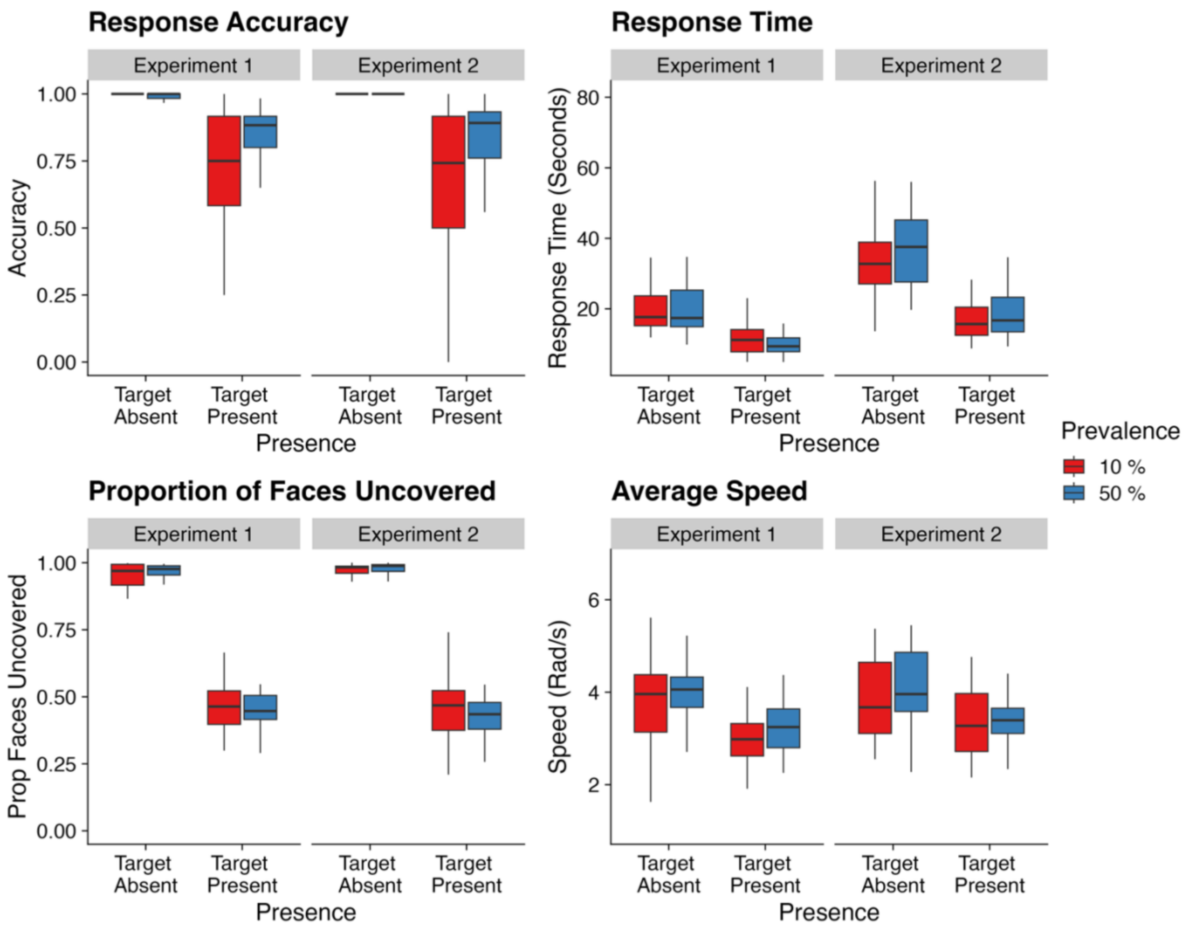
Modelled Effects and Bayes Factors for Experiment 2

	Accuracy				RT		
Parameter	*Estimate*	*CI*	BF_{10}	*OR*	*Estimate*	*CI*	BF_{10}
Intercept	3.36 (0.19)	**2.99 – 3.75**	**1.24×10^{20}**	28.77	9.90 (0.07)	**9.76 – 10.05**	**7.53×10^{149}**
Prevalence (Low, High)	0.49 (0.35)	-0.20 – 1.18	0.92	1.63	0.08 (0.11)	-0.13 – 0.29	0.14
Presence (Absent, Present)	-3.66 (0.20)	**-4.07 – -3.28**	**4.47×10^{22}**	0.03	-0.73 (0.03)	**-0.79 – -0.67**	**4.96×10^{28}**
Prevalence × Presence	0.81 (0.37)	**0.06 – 1.54**	**3.75**	2.24	0.00 (0.06)	-0.11 – 0.11	0.06
	Visual Information Revealed				Speed		
	Estimate	*CI*	BF_{10}	*OR*	*Estimate*	*CI*	BF_{10}
Intercept	0.77 (0.03)	**0.71 – 0.84**	**1.29×10^{28}**	2.17	3.6 (0.17)	**3.26 – 3.93**	**7.44×10^{21}**
Prevalence (Low, High)	0.03 (0.06)	-0.08 – 0.15	0.07	1.03	0.01 (0.27)	-0.52 – 0.54	0.27
Presence (Absent, Present)	-1.69 (0.06)	**-1.80 – -1.58**	**5.87×10^{35}**	0.18	-0.25 (0.05)	**-0.34 – -0.16**	**3,270**
Prevalence × Presence	0.14 (0.11)	-0.07 – 0.34	0.25	1.15	0.12 (0.09)	-0.07 – 0.30	0.20

Note. CIs = Credible Intervals; BF = Bayes Factor; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. All R-Hat values = 1.00. Effects were deemed reliable if CIs did not pass through zero and BF > 3.00. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite. E.g., participants were less likely to be correct in target-present trials than they were target-absent trials.

Figure 2.3

Response Accuracy Rates, Response Times, Proportion of Faces Uncovered as a function of Presence, Prevalence, and Experiment



Note. Box plots display descriptive statistics for each analysis within the current studies. Whiskers indicate the maximum and minimum values of each group.

Overall, then, participants were exhaustive in their searches and typically refused to terminate a target-absent trial before having revealed all faces of each cube. Unlike visual search, target prevalence did not influence participants' willingness to conduct an interactive search exhaustively, nor did it influence the speed at which they interacted with objects.

2.4 Discussion

Our goal here was to examine exhaustiveness in interactive search, focusing on whether searchers are less exhaustive when prevalence is low, primarily in terms of behaviour during target-absent trials. We did so across two experiments in which participants completed a varied prevalence (10%, 50%) interactive search for a T shape attached to the side of a set of virtual cubes that could be rotated. In Experiment 2, we increased the number of cubes to search through from four per trial to eight with the goal of taxing the limits of participants' willingness to search exhaustively by increasing the effort required for an exhaustive search.

For both experiments, we found a standard effect of low prevalence on response accuracy, such that low prevalence targets were more likely to be missed than high prevalence targets. This alone replicates the basic findings of visual search experiments. However, to our surprise, we found no evidence in either experiment that RTs were reduced during target-absent trials when prevalence was low, a finding that runs counter to one of the main and highly replicated results in the visual search low prevalence literature (Horowitz, 2017; Rich et al., 2008; Wolfe et al., 2005, 2007). Of course, in comparison to visual search tasks, where RTs are often very quick indeed, the lengthy time required to rotate cubes in this interactive search task may have swamped any relatively small changes in decision criteria introduced from low target prevalence (e.g., Wolfe et al., 2007). Nevertheless, at a basic level this suggests that the effects of low prevalence in interactive search are still fundamentally different to those in visual search. More in depth analyses conducted on both experiments further confirmed this surprising finding: Participants were equally exhaustive in terms of the proportion of cube faces revealed in high and low prevalence across both experiments; participants did not move the cubes faster under the expectation that no target would be present in either experiment when prevalence was low.

Why might it be the case that the effects of target prevalence are somehow so similar (reduced accuracy for low prevalence) but so different (no shift in exhaustiveness) at the same time? One possible answer is that here our set size was not large enough to find evidence of a shift in exhaustiveness. Despite the fact that Experiment 1 presented only four cubes per trial, the true set size of objects to be searched (the Ts and Ls attached to the sides of the four cubes) was 24 items per trial, similar to that of a normal visual search task (e.g., Wolfe, 2020). Moreover, we doubled the set size and found a near identical pattern of results for Experiment 2. In fact, to better look into this issue, we compared differences within search exhaustiveness between the two experiments to better confirm the influence of changes in set size (see Table 2.4). As with all other analyses, we again found no evidence of the influence of prevalence upon search exhaustiveness as measured by the proportion of faces revealed (BF_{10} = 0.10), nor an interaction between prevalence and the set size manipulation (BF_{10} = 0.33). In fact, we found that those within Experiment 2 revealed a greater proportion of faces (~3%) than those within Experiment 1. If anything, then, the increase in set size within Experiment 2 made participants more exhaustive, albeit to a very small extent, and made no difference to the prevalence effect.

Table 2.4

Modelled Effects and Bayes Factors for Set Size Comparison

Parameter	*Estimate*	*CIs*	BF_{10}	*OR*
Intercept	1.67 (0.05)	**1.58 – 1.76**	$\mathbf{1.02 \times 10^{40}}$	5.31
Prevalence (Low, High)	0.02 (0.09)	-0.16 – 0.21	0.10	1.02
Experiment (One, Two)	0.73 (0.09)	**0.55 – 0.92**	$\mathbf{1.75 \times 10^{7}}$	2.08
Prevalence × Experiment	-0.20 (0.19)	-0.58 – 0.17	0.33	0.82

Note. CIs = Credible Intervals; BF = Bayes Factor; OR = Odds Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. All R-Hat values = 1.00. Effects were deemed reliable if CIs did not pass through zero and BF > 3.00. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite.

Instead, we conclude that, during interactive search, even when prevalence is low, searchers operate under a ‘no stone unturned’ approach. Under this approach, it seems to be the case that searchers are unwilling to provide an ‘absent’ response without checking most – if not all – possible places, regions or areas in a display that could contain a target. This is particularly interesting because it demonstrates that even well-established findings in visual search do not replicate or translate to interactive search. Moreover, it demonstrates that searchers are unwilling to terminate a search based on partial or incomplete information (i.e., they need to experience some sense of checking the entire environment including hidden areas).

Textbooks or introductory chapters often begin by providing examples of visual search that are in fact interactive. For example, in Chun and Wolfe (1996), the authors state within the second sentence of their manuscript: “You are searching for that piece of paper among a mess of various articles, journals, forms, and other miscellaneous paperwork on your desk”. This is undoubtedly a task that typically requires interaction. Likewise, Eckstein (2011) suggests that searching for “one's vehicle in a parking lot” or “keys in a living room” are both examples of visual search. However, when carefully considering these tasks, both require body movements and interactions to locate these targets. The authors cited here are of course in no way intentionally deceiving readers, but it does highlight the need for careful consideration of the differences between interactive and visual search. Perhaps, as we have shown here, further careful study and experimentation will demonstrate that visual search is in fact not a good approximation of interactive search after all.

Chapter 3 Easy Does It: Selection During Interactive Search Tasks is Biased towards Objects that can be Examined Easily

Notes

This chapter was published as an empirical paper and is available online at:

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CRediT (Contributor Roles Taxonomy)

Dewis: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, validation, writing – original draft preparation. Godwin: Conceptualization, investigation, methodology, project administration, resources, software, supervision, validation, writing – review & editing. Metcalf: writing – review & editing, supervision. Warner: writing – review & editing, supervision. Polfreman: writing – review & editing, supervision.

Open Practice Statement

The raw trial data for both experiments, the final processed datasets, and all associated code used for processing and analysing the data is freely available on the Open Science Framework at https://osf.io/2zyvf/

Abstract

It is well understood that attentional selection is required to deploy visual attention to relevant objects within displays during visual search tasks. Interactive search, an extension of visual search, refers to tasks wherein an individual must manipulate items within their environment to uncover obscured information whilst searching for a target object. Here, we conducted two independent interactive search experiments where participants were asked to interact with virtual cubes to locate a target T shape embedded onto the side of one of the cubes. Our goal here was to investigate the drivers of attentional selection within interactive searches. To do so, we manipulated the effort required to rotate cubes (Experiment 1) and the quantity of shapes attached to the cubes (Experiment 2). Our findings suggest that the perceived effort required to interact with an object is an extremely strong driver of attentional selection within interactive search behaviours. Here, targets may be slower to be detected when that target is obscured within or by an object that conveys, in some shape or form, greater difficulty to examine compared to other objects. These findings provide an exciting first step towards understanding the factors that influence selection during interactive searches.

Keywords: Interactive Search, Visual Search, Guided Search, Attentional Selection

3.1 Introduction

You are late for work, and you cannot remember where you placed your car keys. You start rummaging through your desk, picking up books, moving piles of notes, frantically trying to find where you left them. This scenario is an example of an interactive search task: a task wherein the observer must manipulate items or physically change their viewing position to uncover hidden or obscured information whilst searching for a target (Sauter et al., 2020). A handful of studies have investigated interactive search in detail, ranging from simple tasks such as searching for marbles (Gilchrist et al., 2001) or LEGO® bricks (Hout et al., 2022; Sauter et al., 2020), to more societally important and complex tasks such as police personnel searching through houses for drugs and weapons (Riggs et al., 2017, 2018). Interactive searches are not limited to only the physical domain but are commonplace in virtual environments as well where individuals will typically manipulate and change visual displays (Drew et al., 2013; Godwin et al., 2024; Solman et al., 2012, 2013).

The study of interactive search is an extension of visual search, one of the most extensively studied tasks in cognitive psychology (Chan & Hayward, 2013; Wolfe, 2020). In visual search, it has long been known that it is impossible to process all items within the visual field at once, and instead visual attention must be deployed to subsets of objects in the visual display.

Early models of visual attention characterised this process as a dichotomy between top-down and bottom-up control (Corbetta & Shulman, 2002; Itti & Koch, 2000; Wolfe, 1994). Here, top-down input describes the current goals of the searcher, e.g., searching for a red object, and bottom-up input describes the physical salience of a stimulus, e.g., a bright object amongst dull objects, a horizontal line amongst vertical lines, and so forth.

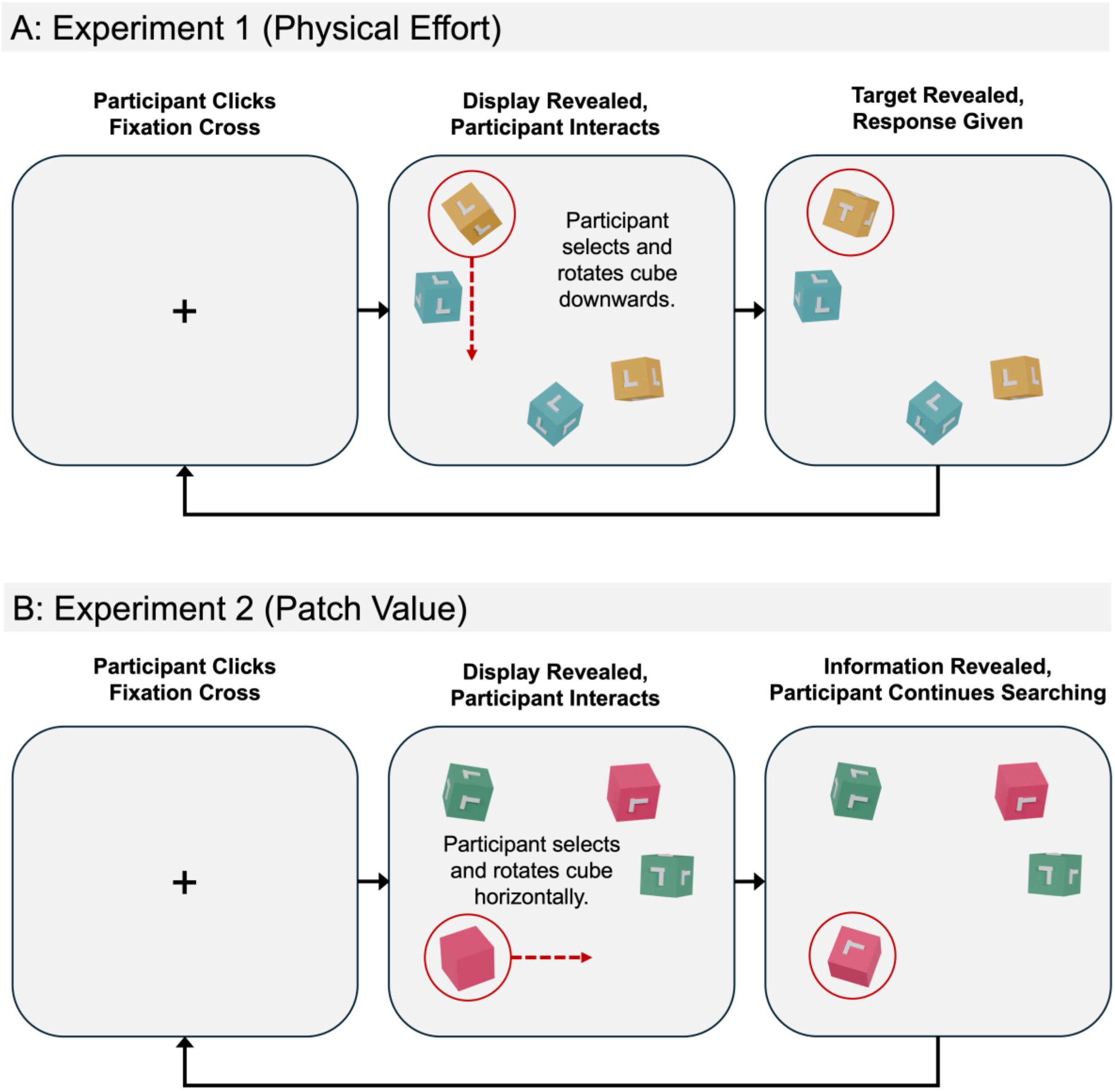
It was widely believed that these top-down and bottom-up inputs combined to create an attentional "priority map" which dictated where visual attention should be deployed (Wolfe, 1994). However, later research made it clear that the deployment of visual attention could not be entirely explained via this top-down/bottom-up dichotomy. Summarising the issues relating to this, Awh et al. (2012) argued that models at the time were too simplistic to account for scenarios wherein attentional selection biases could not be attributed to either top-down nor bottom-up control. As such, they presented a model that included new sources of input to the attentional selection process. These new sources were grouped together under the heading of "selection history", a new category to account for the effects of priming (e.g., Maljkovic & Nakayama, 1994) and reward (Anderson et al., 2011; Hickey et al., 2010b, 2010a, 2015) on attentional control. More recently, Wolfe (2021) expanded upon these sources of input, and suggested that attentional control is influenced by five factors: top-down control, bottom-up control, history (priming), value (reward), and scene guidance. Here, scene guidance refers to the utilisation of previously learned semantic knowledge about the world to guide visual attention away from areas where targets are unlikely to be (e.g., Henderson & Hayes, 2017; Le-Hoa Võ & Wolfe, 2015; Pedziwiatr et al., 2021; Võ et al., 2016; Võ & Wolfe, 2013; Wolfe et al., 2011). Overall, it is now generally understood that in addition to top-down and bottom-up control, many factors work in tandem to influence attentional selection via a priority map (Godwin et al., 2014; Wolfe, 2021; Wolfe & Horowitz, 2017).

There is, to our knowledge, very little research examining the factors that influence selection during interactive search. Here, our goal was to test whether two new sources of input could guide selection during interactive search. These two new sources of input were physical effort and patch value. Here, physical effort refers to the energetic expenditure required to interact with objects and patch value is an established term within the foraging literature which describes the perceived value assigned to different objects/areas containing resources (e.g., Charnov, 1976). However, it is important to note that we are not the first to consider the role of effort and patch value within decision making. Research by Bustamante et al. (2023) has explored their roles within a virtual foraging task for fruit and found effort to cause considerable variation within motivation when foraging. Whilst useful, this research focuses largely on resource depletion when foraging and shows little consideration to the physical interactions required within interactive search nor how they may guide selection biases.

With this in mind, we examined these two new sources of input by conducting two interactive search experiments using a novel methodology wherein participants interactively searched for a target T shape amongst distractor L shapes embedded onto the sides of a set of virtual cubes. Participants interacted with cubes by rotating them with their computer mouse. Here, when a participant clicked on a cube and simultaneously dragged their cursor across the display, the selected cube rotated in the direction of the cursor movement. To ensure effortful interaction, cubes only rotated during cursor movements. In Experiment 1, we manipulated physical effort by making 50 % of the cubes 'heavy' to rotate and 50 % 'light'. In Experiment 2, the resources used to influence patch value was the number of shapes embedded onto the sides of the cubes. Here, 50 % of cubes were made to be 'information-rich' by embedding a shape onto each cube face and 50 % were made to be 'information-poor' by embedding a single shape onto only one of their six possible faces. Across both experiments, we utilised colour to encourage participants to form associations between different cube types (i.e., assigning a blue colour to heavy cubes and a yellow colour to light cubes in Experiment 1, or a green colour to information-rich cubes and a pink colour to information-poor cubes in Experiment 2). Examples of trials from both experiments are depicted in Figure 3.1 and demonstrations of the experiments with a small number of trials can be found here.

Figure 3.1

Trial Structure and Procedure for Experiment 1 and Experiment 2



Note. Figure depicts the procedure of a typical trial for both Experiment 1 and Experiment 2. The red circles and arrows were not visible to the participant and are included here to aid visibility. Participants used their cursor to click on a fixation cross presented in the middle of the screen to start a trial, the display was then revealed, participants then interacted and rotated cubes using their cursor, once the target was found (or deemed absent) the participant ended the trial with a keyboard press. This whole process then repeated for 120 trials.

3.1.1 Physical Effort

In visual search tasks, very little physical effort is required to search. Eye movements are the most common of all behaviours (Bargary et al., 2017) and require very little energetic expenditure to conduct (Araujo et al., 2001). In contrast, interactive search tasks often require energetic expenditure via body movements; typically, the upper limbs, as individuals manually manipulate objects with their hands. It is well established that individuals will try to minimise engaging in tasks that require high energetic expenditure (Anderson et al., 2025; Klein-Flügge et al., 2016; Kurniawan et al., 2010; Prévost et al., 2010). Indeed, perceived physical effort has been shown to further influence engagement in safe versus dangerous work practices (Wickens, 2014), the limbs used to reach and grab objects (Morel et al., 2017; Wang et al., 2021), and the decisions made in complex workspaces such as airplane cockpits (Steelman et al., 2011; Wickens, 2015).

In the context of interactive searches, reducing the number of high effort tasks one engages in is logical, given that there are two dissociable cognitive processes that must work in tandem when doing so: the action system for body movements and the identification system for target detection (Goodale & Milner, 1992; Jeannerod, 1994; Solman et al., 2012). In cases where high physical effort is involved, more resources must be provided to the action system, thus, likely impairing the identification system. This is neatly highlighted in a study by Park et al. (2021). Here, participants were asked to engage in a visual search task whilst simultaneously gripping a "handgrip" device. Whilst searching, participants had to either grip the device with a high grip force (analogous to high physical effort) or a low grip force. In high grip force trials, participants were more prone to interreference from distractors in comparison to the low grip force trials. Overall, then, it seems likely that in scenarios where the likelihood of uncovering a target is equal between objects, attentional deployment should be biased towards objects that indicate a low level of physical effort to interact with.

3.1.2 Patch Value

Patch value is an established term within the foraging literature, and it describes the perceived value assigned to different areas containing resources (e.g., Charnov, 1976). The foraging literature has historically focused on the criteria animals and individuals use to determine when to leave the current patch that they are obtaining resources from (Charnov, 1976; Ehinger & Wolfe, 2016; Wolfe, 2013; J. Zhang et al., 2017). The perceived value assigned to specific patches can be influenced by a range of factors (e.g., Bettinger & Grote, 2016; Charnov, 1976; Eliassen et al., 2009; Norberg, 1977), including the quantity of resources one can obtain from a specific patch (Bremset Hansen et al., 2009; Fryxell, 1991; Van Beest et al., 2010). Here, greater value is given to patches containing large quantities of resources (Bremset Hansen et al., 2009).

This bears particular importance when considering interactive search tasks. Here, we propose that interactive search tasks can be further conceptualised as a form of foraging task where searchers must make decisions regarding patch value (Bella-Fernández et al., 2022; Nahari & El Hady, 2025). When searching, individuals must manipulate and move objects to reveal either other obscured items or sections currently not visible to the searcher, i.e., inside an object, behind an object, and so on. However, instead of foraging for food, searchers here are instead foraging for visual information (Nahari & El Hady, 2025). As such, it seems likely that should searchers attempt to be optimal in their search strategy and follow the same rules found within the foraging literature (e.g., Ehinger & Wolfe, 2016), then they should bias their searches towards areas that are resource-rich and capable of providing large quantities of information to the searcher. Likewise, this also makes sense at a probabilistic level: if one does not know where a target may appear, focusing on areas with the largest number of potential targets would be a far more efficient strategy than focusing on those areas with only a small number of potential targets.

3.2 Experiment 1: Physical Effort

In Experiment 1, we started by investigating the role of physical effort within interactive search. Based on the previously mentioned literature, we predicted that within our experiment, due to the increased physical effort required to rotate heavy cubes, participants would become more likely to examine the light cubes first within each trial. Likewise, due to the increased effort associated with heavy cubes, we further predicted that participants would become less exhaustive in their searching of heavy cubes, as evidenced by a reduction in the number of cube faces a participant revealed and viewed throughout a trial.

3.3 Method

3.3.1 Ethical Approval

Ethical approval was given for Experiment 1 by the University of Southampton’s Ethics Committee on the 26th of September 2023 (ERGO NUMBER: 95398.A1).

3.3.2 Participants

A priori power analyses were conducted using the *SIMR* package in R (P. Green & MacLeod, 2016) on pilot data from 15 participants. To avoid the issues associated with “observed power” (see Hoenig & Heisey, 2001 for an explanation), target effect sizes were loosely informed by prior research (Godwin et al., 2024). Due to the limited previous research within this area, we chose a medium standardised effect size. Power analyses were conducted for the first dependent variable being analysed and a minimum sample size of 35 participants was recommended to obtain a power level of 0.80.

A total of 40 participants were recruited from the University of Southampton. Of this sample, ages ranged from 18 to 21 (M = 18.88, SD = 0.99). Seventy-five percent of the sample were female, 22.50 % were male, and 2.50 % were non-binary.

3.3.3 Stimuli and Apparatus

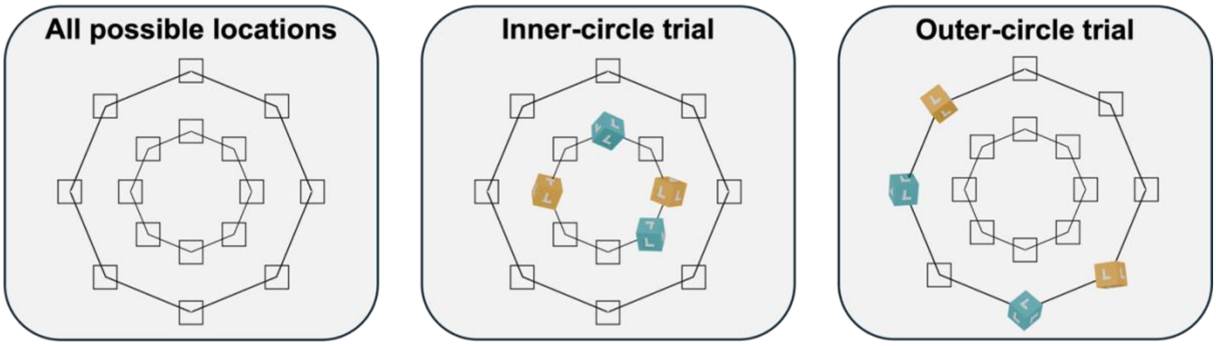
Stimuli were created using the open-source software Blender (Hess, 2010). Displays consisting of these stimuli were then generated using Three.js (an open-source JavaScript library for displaying three-dimensional graphics within web browsers; Danchilla, 2012) and embedded into a standard jsPsych framework (an open-source JavaScript library for building web-based psychological experiments; De Leeuw, 2015).

The stimuli for Experiment 1 consisted of four different types of virtual cubes: heavy and light cubes containing an L distractor shape on each of their six faces, and heavy and light cubes containing a distractor L shape on five of their six faces and a single target T shape on the remaining sixth face. Heavy and light cubes were assigned a single independent colour at the start of the experiment which did not change throughout the remainder of the experiment. This was to ensure that participants would associate a specific cube colour with the effort required to rotate them. Colours were selected from a list of 16 ordered colours used in previous visual search experiments (e.g., Menneer et al., 2007; Stroud et al., 2012). Each consecutive colour was approximately equally spaced from the previous in CIE xyY space. The colour chosen for heavy cubes was randomised for each participant to reduce any risk of biases towards specific colours. The colour selected for the light cubes was always eight steps away from the previously selected heavy cube colour in the colour list. This ensured that colours were as maximally different as possible to help strengthen the association between colour and effort.

Each search display contained two heavy and two light cubes, each of which were randomly assigned to one of eight possible locations on the screen and then randomly rotated through each of their axes by up to 360º. As shown in Figure 3.2, on each trial, cubes were placed within one of two concentric circles (inner or outer) each of which contained eight equidistant locations. A single trial could not contain cubes in both the inner and outer circles simultaneously. This was to ensure that the distance from the centre of the screen to each cube was equal at the start of the trial to reduce the likelihood that participants would simply interact with the cube closest to the centre. Fifty percent of trials were inner-circle trials and 50 % were outer-circle trials. The order in which trials were presented was randomised.

Figure 3.2

Cube Placing Procedure



Note. Figure depicts all the possible locations that cubes could have been placed for each trial. The outlines of the circles and locations were not visible to the participant. Participants had to use their cursor to click on a fixation cross presented in the middle of the screen before a display was revealed, this was to ensure that their cursor starting position would be from the centre of the screen for each trial.

Participants completed the study using their own computers or laptops. They were informed to press the M key of their keyboard if they believed that the display contained a target and the Z key if they believed the display did not contain a target. Participants interacted by clicking on a cube and simultaneously dragging their cursor across the screen. Here, when the participant clicked and dragged their cursor, the selected cube rotated in the direction of the cursor movement. A cube only rotated whilst the participant was clicking and dragging.

3.3.4 Design and Procedure

Once participants consented to taking part, they were provided with detailed instructions on what was required to complete the experiment, followed by a training segment wherein participants could learn and practice how to rotate cubes with their computer mouse. Following this, participants completed five practice trials with accuracy feedback before starting the real trials which contained no feedback. All participants then completed a total of 120 trials. Before each trial, participants had to click a fixation cross to reveal the display. The display then remained on screen until the participant made a response to end the trial. Following a participant response, the next trial's fixation cross was displayed, and the process repeated. This process is depicted in Figure 3.1A.

A target cube was present on 50 % of the 120 search trials and absent on the remaining trials. The order in which participants completed trials was randomised. Within each trial, two of the four cubes were always substantially more difficult to rotate than the other two cubes. This was achieved by reducing the cursor sensitivity whenever a participant interacted with these heavy cubes, resulting in the cubes rotating at a slower rate and thus requiring ~2-3 times the number of clicks and drags to rotate them by the same magnitude as a light cube. The same colour contingencies were used during the practice trials as were during the real trials. All stimuli were evenly split between heavy and light conditions.

3.4 Results

3.4.1 Data Cleaning

Before any analyses, all data underwent preplanned cleaning procedures based on those used in prior online search experiments (Godwin et al., 2024; Godwin & Hout, 2023). A breakdown for the number of participants/trials removed at each stage of cleaning can be found in Table 3.1.

Table 3.1

Data Cleaning Steps for Each Experiment

	Experiment 1 (Effort Manipulation)		Experiment 2 (Information Manipulation)	
Removal Step	**Trials Removed**	**Remaining Trials**	**Trials Removed**	**Remaining Trials**
Raw Data	0 (0.00 %)	4,800 (100 %)	0 (0.00 %)	5,400 (100 %)
Fast/Slow Trials	20 (0.42 %)	4,780 (99.58 %)	1 (0.02 %)	5,399 (99.98 %)
Guessing Trials	11 (0.23 %)	4,769 (99.35 %)	2 (0.04 %)	5,397 (99.94 %)

Note. Fast trials = trial response times < 250 ms; Slow Trials = trial response times > 60,000 ms; “Guessing Trials” refers to target-present trials in which participants responded present yet never revealed the face of the cube containing the target.

No participants were removed from either dataset.

First, trials shorter than 250 ms or longer than 60 seconds were removed from the dataset. The upper limit of this criterion was decided upon from what we deemed to be an acceptable time to have exhaustively checked all four cubes. Likewise, it was implausible that a participant would be able to engage with the array and respond in under 250 ms. Finally, any trials where a participant had responded that the target was present but never revealed the face of the cube containing the target T shape, were removed from the dataset.

After all cleaning steps, the final dataset consisted of 4,769 trials from 40 participants.

3.4.2 Analytic Approach

All effects were modelled through Bayesian generalised linear mixed effects models (BGLMM) via the *brms* package in R (Bürkner, 2017; R Core Team, 2023). The reliability of effects was confirmed using Bayes factors, calculated via the *bayestestR* package in R (Makowski et al., 2019). Bayes factors greater than 1.00 indicate stronger evidence towards the alternative hypothesis and Bayes factors less than 1.00 suggest stronger evidence towards the null hypothesis. For the purpose of the discussion, we have deemed an effect to be trustworthy if both its 95 % credible interval (CI) did not pass through zero, and it possessed a Bayes factor of greater than 3.20.

Where relevant, models used the following fixed factors: Presence (Absent, Present), Trial Index (a continuous value used as a measure of time through experiment), Effort Type (Heavy, Light), and Next Closest Object Type (Heavy, Light). Across all analyses, Trial Index was rescaled and centred to improve model fitting and interpretation (Kreft et al., 1995). Each model included random intercepts and slopes for Participant ID and Presence. This allowed for individual variation between participants and trial types within each model. Models that did not use a full random structure did so due to model fitting errors. When models with full random structure returned fitting errors, the random structures were trimmed from the model until model fitting errors no longer occurred. Relatively flat priors were chosen for all analyses due to the novel and exploratory nature of the study and associated analysis (e.g., very little is known regarding first and second interaction choices within interactive search).

The likelihood of a participant selecting a light cube was calculated by coding any interaction with light cubes as a 1 and any interactions with heavy cubes as a 0. This was then modelled using a Bernoulli distribution with a logit link function. Likewise, a Poisson distribution was used to model the total number of cube faces viewed by participants. Our analyses focused only on participants' first and second interactions. Our reason for doing so was that since each trial contained only four cubes, the third and fourth interactions were typically a mirror of the first and second interactions. For example, if a participant's first two interactions were to the two light cubes, then their remaining interactions would be to the two remaining heavy cubes and vice versa.

Each model was fitted using four chains, with 11,000 iterations and 1000 warmup iterations to allow for accurate Bayes factors (Makowski et al., 2019). All Gelman-Rubin statistics were below 1.10 for all parameters and visual inspection of the chains indicated good mixing.

3.4.3 Response Accuracy and Response Times

Overall, for target-absent trials, participants had high accuracy with few false alarms (M = 0.98, SD = 0.13) and completed the trials within a reasonable time (M = 20,609.03 ms, SD = 7,388.47 ms). For target-present trials, participants had good accuracy (M = 0.92, SD = 0.27) and completed trials within a reasonable time (M = 9,775.11 ms, SD = 7,201.42 ms). We carried out no further analyses on response accuracy or response times. Our remaining analyses focused on the order of interactions and search exhaustiveness.

3.4.4 First Interaction Choice

Our first analysis focused on the likelihood of a participant selecting a light cube as their first interaction of a trial. Model effects and their corresponding CIs and Bayes factors can be found in Table 3.2 and descriptive statistics in Figure 3.3.

Table 3.2

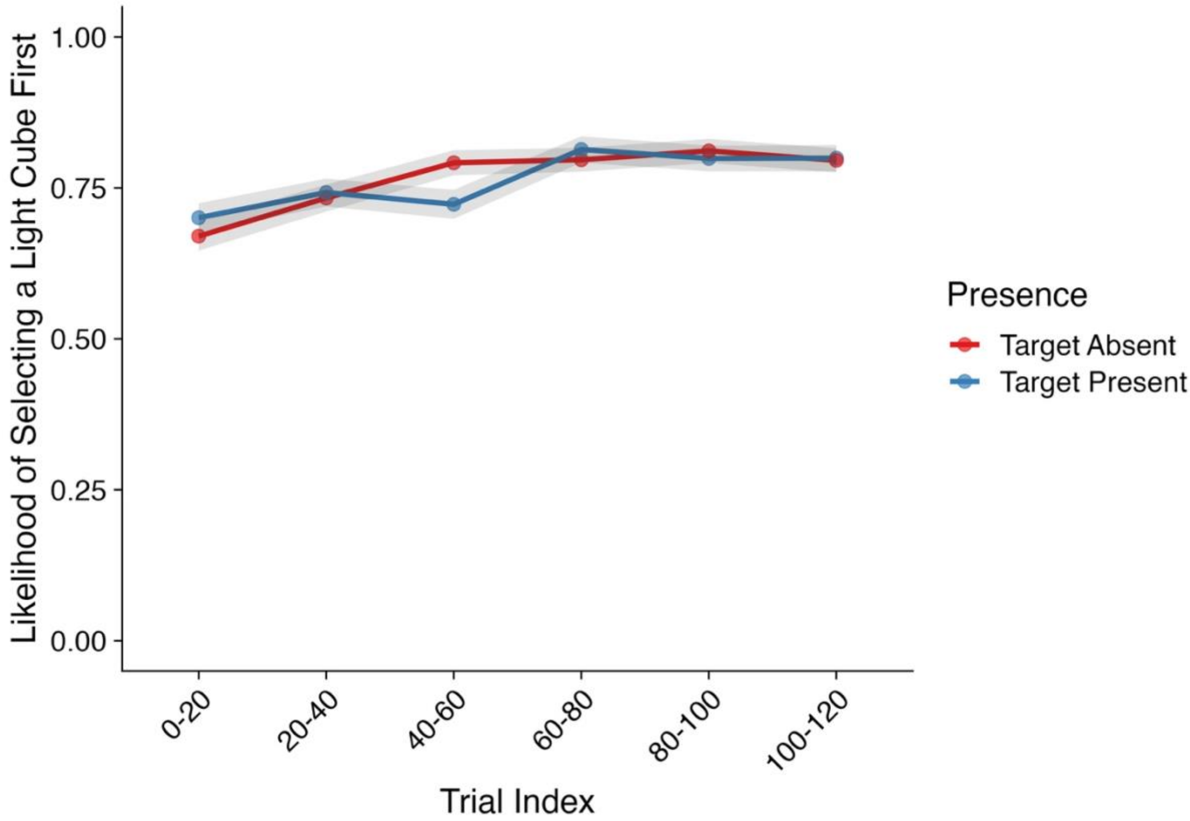
Model Effects and Bayes Factors – Likelihood of Selecting a Light Cube First

Parameter	***Estimate***	***CIs***	***R-Hat***	***BF₁₀***	***OR***
Intercept	1.04 (0.22)	**0.62 – 1.47**	1.00	**6.58×10^{3}**	2.84
Presence (Absent – Present)	0.02 (0.15)	-0.29 – 0.32	1.00	0.16	1.02
Trial Index	0.52 (0.08)	**0.37 – 0.68**	1.00	**5.16×10^{5}**	1.68
Presence × Trial Index	-0.08 (0.16)	-0.38 – 0.23	1.00	0.17	0.93

Note. CIs = Confidence Intervals; BF = Bayes factor; OR = Odds Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite.

Figure 3.3

Likelihood of Selecting a Light Cube First (Experiment 1)



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error.

We observed a strong main effect of Trial Index on the likelihood of a participant selecting a light cube first, with no other effects emerging. Here, participants became substantially more likely to select a light cube first as the experiment progressed. As can be seen in Figure 3.3, across the first 20 trials, participants' likelihood of selecting a light cube first was ~0.67 for target-absent trials and ~0.70 for target-present trials. By the time participants reached the end of the experiment, this likelihood increased substantially to ~0.80 for both target-absent and target-present trials.

3.4.5 Second Interaction Choice

Our next analysis focused on the likelihood that the second cube a participant examined would also be a light cube. Here, we focused only on trials where participants did not find the target within their first interaction. At the start of each trial, the participant had to click on a central fixation cross to reveal the display. As such, a participant's attention should have been focused on the centre of the display (Anwyl-Irvine et al., 2021). For each trial, all cubes were equidistant from the centre of the display, thus reducing the likelihood that participants would simply select the closest cube to their current position. However, after a participant had made their first interaction, the distance of other cubes from their current position was no longer equidistant. As such, a participant may have been influenced to interact with cubes that were closer to their current position and adopt a 'nearest next' strategy. Therefore, an additional factor was included in the model which measured whether the next closest cube to the previous interaction was either a heavy or light cube. Model effects and their corresponding CIs and Bayes factors can be found in Table 3.3 and descriptive statistics in Figure 3.4.

Table 3.3

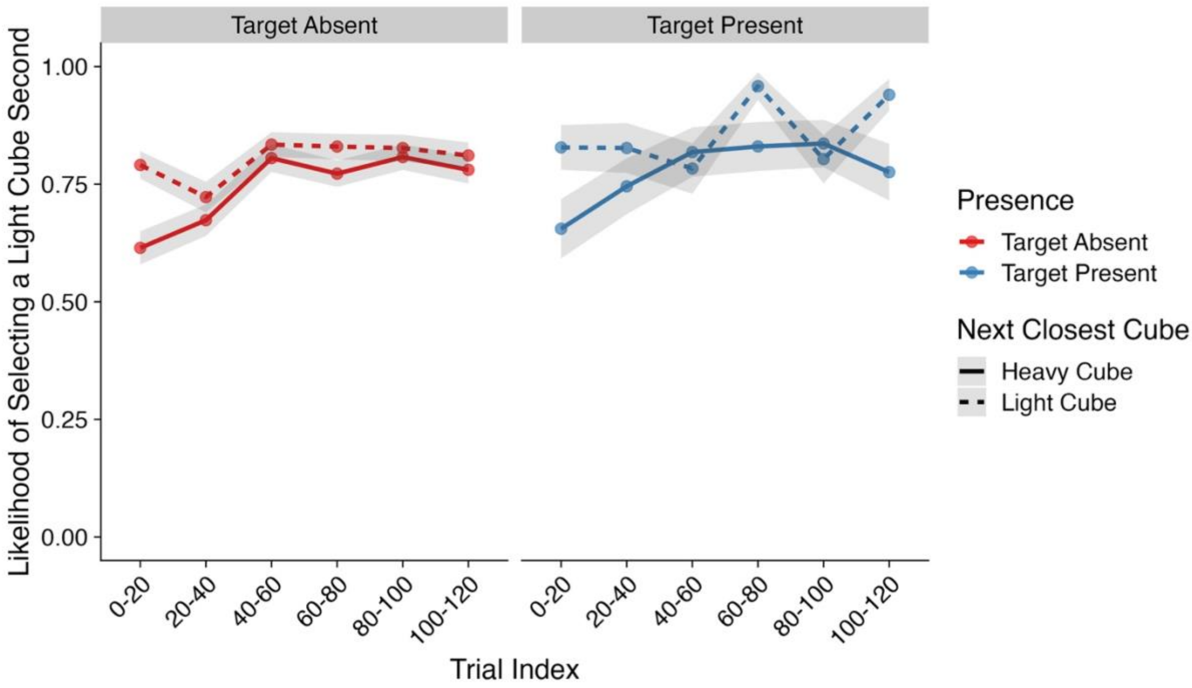
Model Effects and Bayes Factors – Likelihood of Selecting a Light Cube Second

Parameter	***Estimate***	***CIs***	***R-Hat***	***BF_{10}***	***OR***
Intercept	1.36 (0.29)	**0.79 – 1.95**	1.00	**585.01**	3.91
Presence (Absent – Present)	0.30 (0.24)	-0.16 – 0.78	1.00	0.52	1.35
Trial Index	0.63 (0.13)	**0.37 – 0.89**	1.00	**1.92×10^3**	1.88
Next Closest Object Type (Heavy – Light)	1.03 (0.22)	**0.60 – 1.47**	1.00	**3.20×10^3**	2.81
Presence × Trial Index	0.11 (0.26)	-0.40 – 0.61	1.00	0.28	1.11
Presence × Next Closest Object Type	-0.07 (0.41)	-0.86 – 0.74	1.00	0.41	0.94
Trial Index × Next Closest Object Type	-0.15 (0.24)	-0.63 – 0.33	1.00	0.29	0.86
Presence × Trial Index × Next Closest Object Type	0.39 (0.44)	-0.48 – 1.25	1.00	0.66	1.48

Note. CIs = Confidence Intervals; BF = Bayes factor; OR = Odds Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite.

Figure 3.4

Likelihood of Selecting a Light Cube Second (Experiment 1)



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error.

Within this analysis, two main effects were observed. First, participants became more likely to select a light cube as their second interaction as the experiment progressed. Next, we found a strong effect of Next Closest Object Type on the likelihood of examining a light cube second. Here, participants were more likely to examine a light cube second if the next closest cube to their current position was also a light cube. However, it is worth noting that even on trials where the next closest cube was not a light cube, participants were still ~60-70 % more likely to examine a light cube over a heavy cube. In line with our predictions, these findings further highlight the impact of effort on interaction order.

3.4.6 Number of Faces Viewed

Our final analysis focused how exhaustive participants were as they searched the displays. We measured this in terms of the number of cube faces participants viewed across each trial. For an exhaustive search, we would expect a participant to have viewed 6 faces per cube, or 12 faces per cube type (i.e., heavy versus light). Model effects and their corresponding CIs and Bayes factors can be found in Table 3.4 and Descriptive statistics in Figure 3.5.

Table 3.4

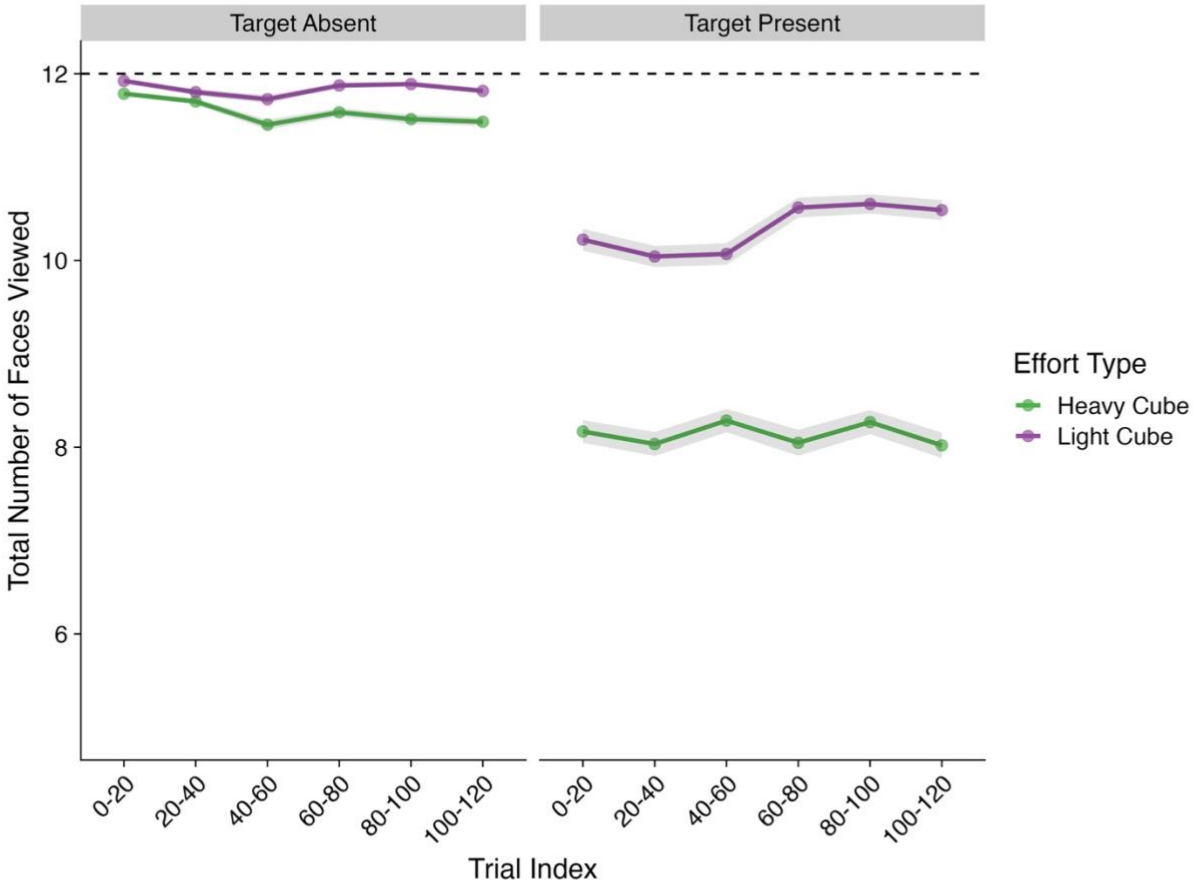
Model Effects and Bayes Factors – Total Number of Faces Viewed Per Cube Type

Parameter	***Estimate***	***Cis***	***R-Hat***	***BF_{10}***	***IRR***
Intercept	2.34 (0.01)	**2.32 – 2.35**	1.00	**Inf**	10.33
Presence (Absent – Present)	-0.27 (0.01)	**-0.29 – -0.24**	1.00	**7.26×10^{20}**	0.77
Trial Index	0.00 (0.01)	-0.01 – 0.01	1.00	0.01	1.00
Effort Type (Heavy – Light)	0.10 (0.01)	**0.08 – 0.13**	1.00	**3.32×10^{10}**	1.11
Presence × Trial Index	0.03 (0.01)	**0.00 – 0.05**	1.00	0.17	1.03
Presence × Effort Type	0.19 (0.02)	**0.15 – 0.24**	1.00	**9.18×10^{06}**	1.21
Trial Index × Effort Type	0.03 (0.01)	**0.01 – 0.05**	1.00	0.36	1.03
Presence × Trial Index × Effort Type	0.03 (0.02)	-0.02 – 0.07	1.00	0.05	1.03

Note. CIs = Confidence Intervals; BF = Bayes factor; IRR = Incidence Rate Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20. IRRs have been added to aid interpretation of effects. IRRs indicate how frequently an event happens in one group compared to another. Values > 1.00 indicate greater frequency and values < 1.00 indicate the opposite.

Figure 3.5

Total Number of Faces Viewed ~ Effort Type (Experiment 1)



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error. Total viewed faces are summed and averaged for each cube type. Dashed line indicates the max number of potential faces a participant could view for each cube type.

For this analysis, we observed main effects for Presence and Effort Type, both of which were subsumed by a Presence × Effort Type interaction. Post hoc contrasts were conducted to further understand this interaction. Overall, we observed a clear difference between the number of faces viewed between heavy and light cubes. In target-absent trials, this effect was extremely small, with a Bayes factor below the 3.20 cutoff (*Estimate* = -0.02, *lower CI* = -0.03, *upper CI* = -0.01, BF_{10} = 2.14), however, in target-present trials, this difference was much more substantial (*Estimate* = -0.24, *lower CI* = -0.26, *upper CI* = -0.22, BF_{10} = 1.77×10^{32}). Put simply, participants viewed on average ~2 less cube faces for heavy cubes compared to light cubes but only within target-present trials. Since participants predominantly examined the light cubes first, this reduction in search exhaustiveness was likely a result of participants finding the target before needing to reveal the additional faces of the heavy cubes.

3.5 Discussion

In Experiment 1, participants engaged in an interactive search for a target T shape attached to the side of virtual cubes. Cubes were interacted with by clicking and dragging on them with a computer mouse which resulted in a rotation of the selected cube. On each trial, two of the four potential cubes were made to be physically effortful to interact with by reducing their sensitivity to the computer cursor. Our reasons for doing so were twofold. First, it is generally understood that there are many attributes that contribute towards attentional selection whilst searching (Awh et al., 2012; Wolfe, 2021). Second, previous literature investigating the role of physical effort and energy expenditure has been shown to influence a range of different behaviours (Anderson et al., 2025; Klein-Flügge et al., 2016; Kurniawan et al., 2010; Morel et al., 2017; Prévost et al., 2010; Steelman et al., 2011; Wang et al., 2021; Wickens, 2014, 2015). As such, we believed that when individuals are given a way to associate specific colours with increased physical effort, their attentional selection will become biased by this information with the overarching goal of reducing energetic expenditure.

We found strong evidence in favour of the notion that the effort associated with examining a given object indeed biased attentional selection within interactive searches. Put simply, participants focused on the easy-to-examine light cubes first and then moved towards the more difficult-to-examine heavy cubes later in each trial. This focus on the easy-to-examine cubes grew as the trials progressed. These findings were in line with our predictions. Due to the increased effort required to rotate heavy cubes, we expected participants to search these cubes less exhaustively and thus view fewer of their faces throughout a trial. However, we only observed this in target-present trials. In target-absent trials participant remained exhaustive regardless of the effort condition.

The pattern of these findings provides two main takeaways from this experiment. The first is that the effort required to interact with objects appears to be a very strong driver of attentional selection indeed. It is worth noting here that within the first twenty trials, the likelihood of selecting a light cube first was ~70 %. As such, the bias towards light cubes was learned and applied almost immediately. This is further supported by the fact that when the next closest cube was not a light cube, the likelihood of selecting a light cube was still ~70 % – 75 %. Here, participants would still travel the extra distance to ensure that their second interaction was to the next available light cube. The second is that the increased effort was not enough to deter participants from still examining the heavy cubes. Here, if participants could not find the target on the light cubes, they would still exhaustively examine the heavy cubes.

3.6 Experiment 2: Patch Value

In Experiment 2, we conducted a further study to determine whether perceived patch value influenced attentional selection during interactive search. To do so, we again asked participants to rotate and search through sets of virtual cubes for a T shape embedded onto the side of one of the cubes. Half of the cubes were made to be ‘information-rich’ by embedding a shape to each of their six faces, and the remaining half were made to be ‘information-poor’ by attaching a shape to only one of their six faces (hereafter we refer to these as *rich* and *poor* cubes for brevity).

We proposed that our interactive search task be further conceptualised as a foraging task for visual information (Bella-Fernández et al., 2022; Nahari & El Hady, 2025). With this in mind, the previous foraging literature suggests that individuals should become optimal in their strategies and prioritise patches that are more likely to contain high quantities of the resources they are foraging for (Bremset Hansen et al., 2009; Cain et al., 2012; Fryxell, 1991; Van Beest et al., 2010). As such, we predicted that participants would be more likely to examine the rich cubes before they examined the poor cubes. Likewise, since uncovering the additional blank faces on poor cubes would not result in any new information being uncovered, we further predicted that, compared to rich cubes, participants would be less exhaustive when searching through poor cubes and overall would stop interacting with poor cubes following the reveal of their stimulus.

3.7 Method

All methodological details for Experiment 2 are identical to Experiment 1 except where described below.

3.7.1 Ethical Approval

Ethical approval was given for Experiment 2 by the University of Southampton’s Ethics Committee on the 26th of September 2023 (ERGO NUMBER: 95398.A1).

3.7.2 Participants

As with Experiment 1, *a priori* power analyses were carried out using the *SIMR* package in R (P. Green & MacLeod, 2016) on pilot data from 15 participants. Power analyses were conducted for the first dependent variable being analysed. These analyses revealed that for a power level of 0.80, a minimum sample size of ~35-40 participants was required.

A total of 45 participants were recruited from the University of Southampton. Of this sample, ages ranged from 18 to 21 (M = 19.04, SD = 1.31) with 91.11 % being female, 6.67 % male, and 2.22 % non-binary.

3.7.3 Stimuli and Apparatus

The cubes used for Experiment 2 differed slightly from Experiment 1. We used four different types of cubes: rich and poor cubes containing only distractor L shapes, and rich and poor cubes containing either five L shapes and a single target T shape for rich cubes or a single target T shape for poor cubes. Each cube face had either a single shape attached to them or nothing at all. The same colour contingencies from Experiment 1 were also used for Experiment 2. Within each trial, two of the four cubes were always poor and the other two were rich. All stimuli were evenly split between information types.

3.7.4 Design and Procedure

The procedure for Experiment 2 was identical to Experiment 1 with the only difference being the stimuli used. A typical trial is depicted in Figure 3.1B.

3.8 Results

3.8.1 Data Cleaning

All data underwent the same preplanned cleaning procedures as Experiment 1 before any analyses were carried out (see Table 3.1).

3.8.2 Analytic Approach

For the most part, the same analytic approach from Experiment 1 was used for Experiment 2. All analyses used the same coding methods and model structures as Experiment 1. It is however important to note that the likelihood of selecting a light cube was changed to be the likelihood of selecting an *information-rich* cube. Likewise, the model factor Effort Type was changed to Information Type (Rich, Poor) and the model factor Next Closest Cube Type was changed from light and heavy to poor and rich. In comparison to Experiment 1, we conducted one additional analysis on the time it took participants to stop rotating poor cubes following stimulus reveal. For this analysis, stop times were recorded in ms and log transformed. A gaussian distribution with the log transformed stop times were used to model effects for this measure.

3.8.3 Response Accuracy and Response Times

Overall, for target-absent trials, participants had high accuracy with few false alarms (M = 0.99, SD = 0.09) and completed the trials within a reasonable time (M = 13,298.53 ms, SD = 5,308.53 ms). For target-present trials, participants had good accuracy (M = 0.96, SD = 0.20) and completed the trials at a reasonable pace (M = 6,137.18 ms, SD = 4,719.52 ms). We carried out no further analyses on response accuracy or response times. The remaining analyses focused on the order of interactions and search exhaustiveness.

3.8.4 First Interaction Choice

Our first analysis focused on the likelihood of a participant selecting a rich cube as their first interaction of a trial. Model effects and their corresponding CIs and Bayes factors can be found in Table 3.5 and descriptive statistics in Figure 3.6.

Table 3.5

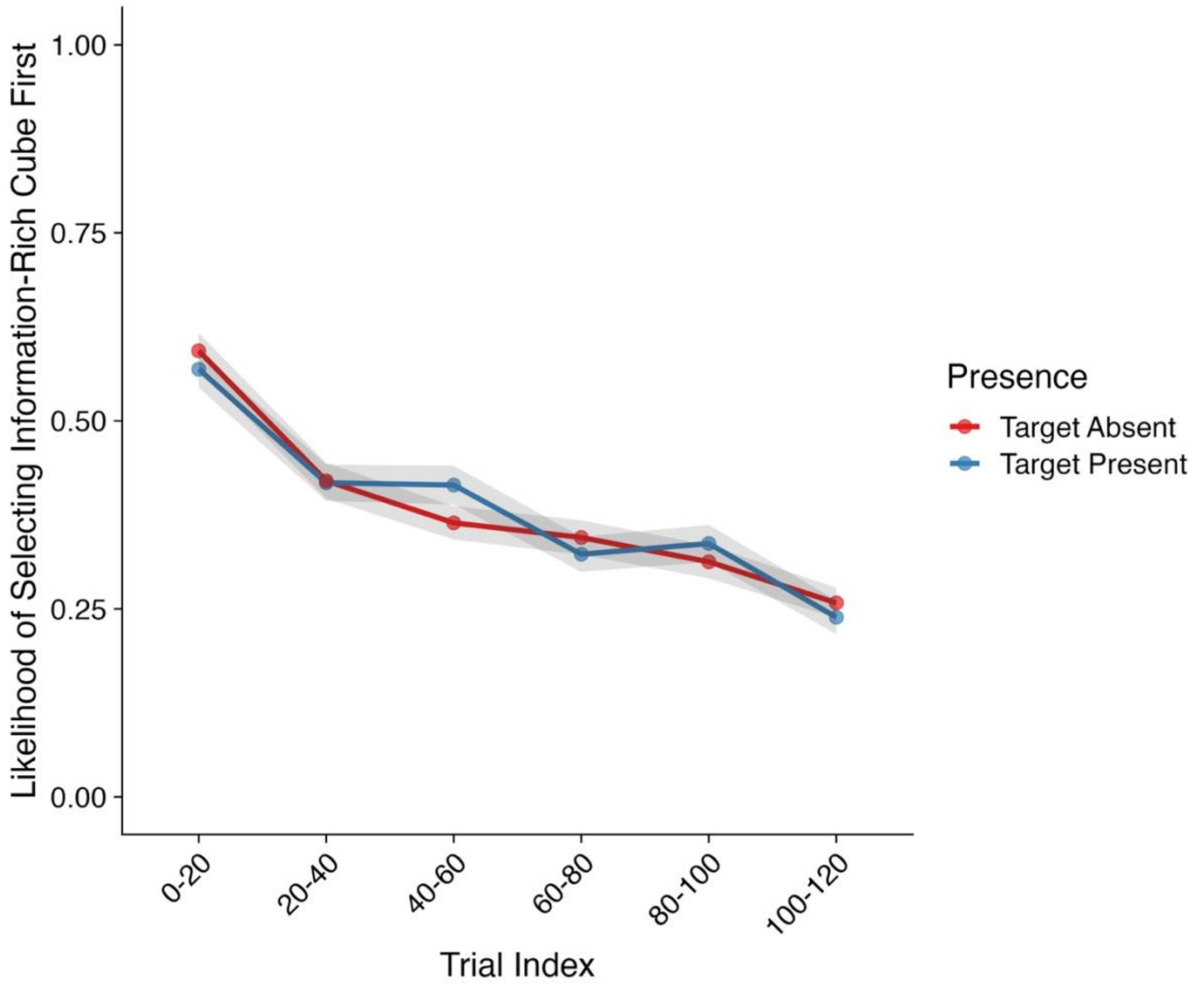
Model Effects and Bayes Factors – Likelihood of Selecting an Information-Rich Cube First

Parameter	***Estimate***	***CIs***	***R-Hat***	***BF_{10}***	***OR***
Intercept	0.36 (0.18)	0.01 – 0.71	1.00	0.50	1.43
Presence (Absent – Present)	0.01 (0.13)	-0.24 – 0.26	1.00	0.13	1.01
Trial Index	-1.10 (0.07)	**-1.23 – -0.96**	1.00	**1.08×10^{20}**	0.33
Presence × Trial Index	-0.01 (0.14)	-0.27 – 0.26	1.00	0.14	0.99

Note. CIs = Confidence Intervals; BF = Bayes factor; OR = Odds Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite.

Figure 3.6

Likelihood of Selecting an Information-Rich Cube First (Experiment 2)



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error.

We observed an extremely strong effect of Trial Index on the likelihood of selecting a rich cube. Here, participants became substantially less likely to select a rich cube first as the experiment progressed. As can be seen in Figure 3.6, regardless of trial type, participants started with a probability of selecting a rich cube of ~0.60 and finished with a probability of ~0.25. This finding was the polar opposite of what we predicted.

3.8.5 Second Interaction Choice

Our next analysis focused on the likelihood of participants selecting a rich cube as their second interaction. To recap, as with Experiment 1, following an initial interaction, cubes were no longer equidistant from a participant's current area of attention. As such, we again included an additional model factor which measured whether the next closest cube to the previous interaction was either a poor or rich cube. This set of analyses only included data from trials where participants had not located the target during their previous interaction. Model effects and their corresponding CIs and Bayes factors can be found in Table 3.6 and descriptive statistics in Figure 3.7.

Table 3.6

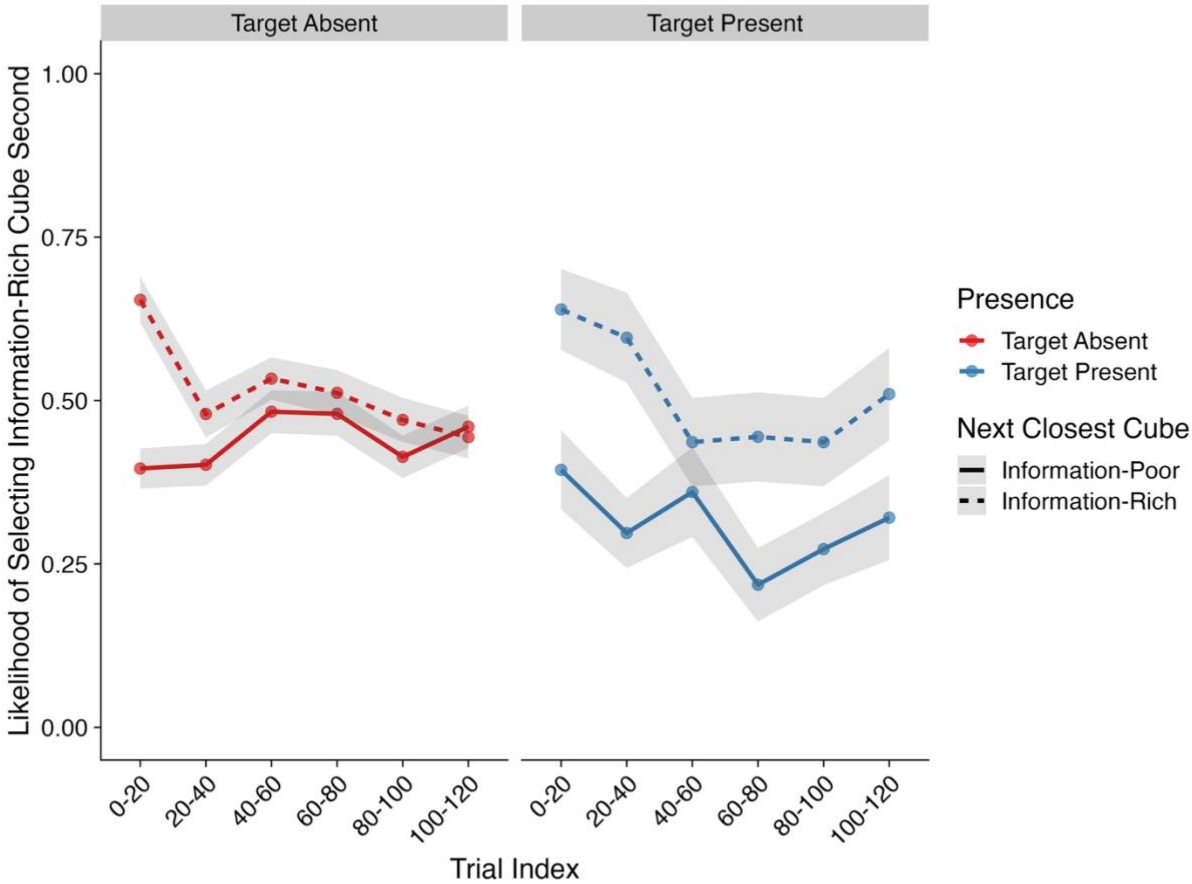
Model Effects and Bayes Factors – Likelihood of Selecting an Information-Rich Cube Second

Parameter	***Estimate***	***CIs***	***R-Hat***	***BF$_{10}$***	***OR***
Intercept	-0.01 (0.16)	-0.32 – 0.31	1.00	0.05	0.99
Presence (Absent – Present)	-0.10 (0.21)	-0.52 – 0.32	1.00	0.23	0.91
Trial Index	-0.33 (0.10)	**-0.53 – -0.14**	1.00	**25.07**	0.72
Next Closest Object Type (Rich – Poor)	1.06 (0.18)	**0.70 – 1.43**	1.00	**4.71×10^5**	2.90
Presence × Trial Index	-0.32 (0.19)	-0.70 – 0.06	1.00	0.76	0.73
Presence × Next Closest Object Type	0.36 (0.35)	-0.32 – 1.04	1.00	0.59	1.43
Trial Index × Next Closest Object Type	-0.34 (0.18)	-0.70 – 0.03	1.00	0.99	0.71
Presence × Trial Index × Next Closest Object Type	0.46 (0.35)	-0.23 – 1.14	1.00	0.82	1.58

Note. CIs = Confidence Intervals; BF = Bayes factor; OR = Odds Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20. ORs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite.

Figure 3.7

Likelihood of Selecting an Information-Rich Cube Second (Experiment 2)



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error.

For this analysis, we observed two main effects: Next Closest Cube Type and Trial Index. First, participants were overall more likely to select a rich cube as their second interaction if the next closest cube to their previous interaction was also a rich cube. Next, when accounting for the effects of Next Closest Cube Type, overall, participants became less likely to select a rich cube as their second interaction as the experiment progressed. This was again not in line with our predictions.

3.8.6 Number of Faces Viewed

Our final analysis focused on a participant's search exhaustiveness as measured by the number of cube faces that a participant viewed throughout a trial. Model effects and their corresponding CIs and Bayes factors can be found in Table 3.7 and descriptive statistics in Figure 3.8.

Table 3.7

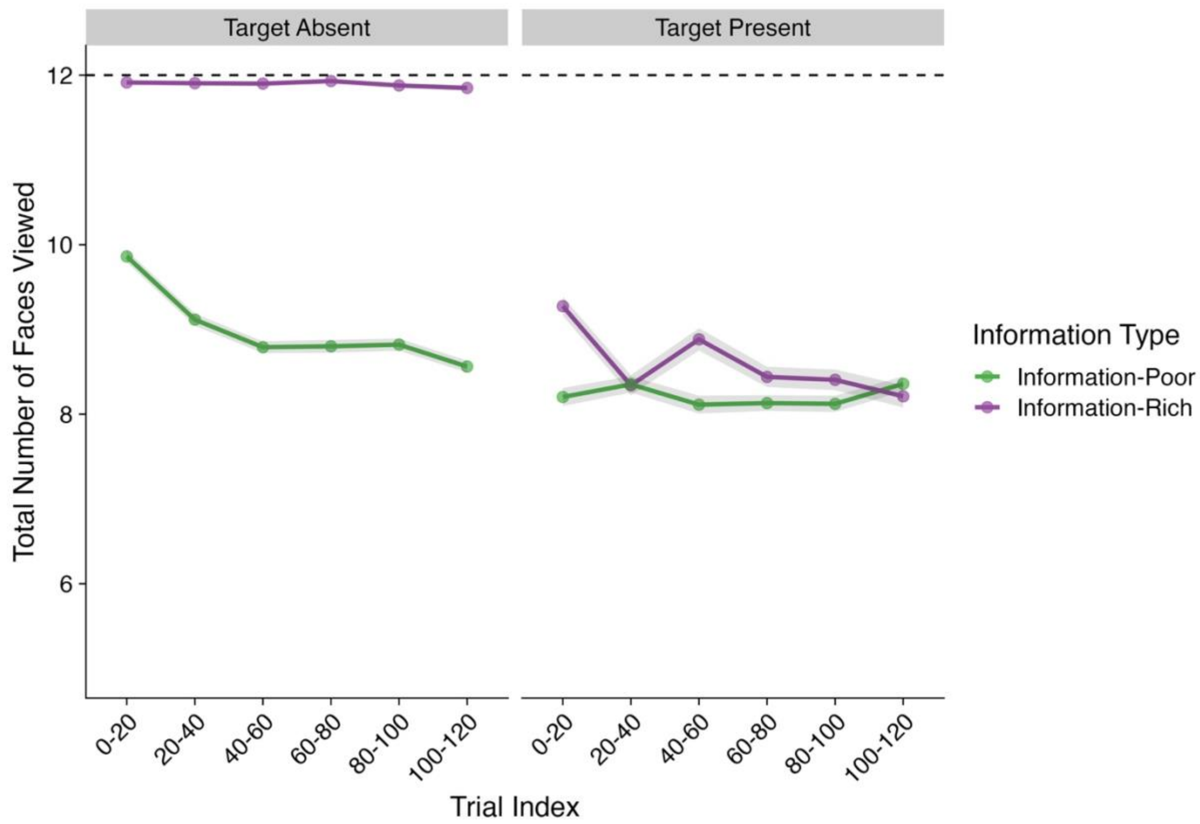
Model Effects and Bayes Factors – Number of Faces Viewed Per Cube Type (Experiment 2)

Parameter	***Estimate***	***CIs***	***R-Hat***	***BF_{10}***	***IRR***
Intercept	2.26 (0.01)	**2.25 – 2.28**	1.00	**Inf**	9.62
Presence (Absent – Present)	-0.22 (0.01)	**-0.24 – -0.19**	1.00	**4.37×10^{22}**	0.81
Trial Index	-0.04 (0.01)	-0.05 – -0.03	1.00	**6.33×10^{5}**	0.96
Information Type (Rich – Poor)	-0.16 (0.01)	**-0.18 – -0.14**	1.00	**3.03×10^{14}**	0.85
Presence × Trial Index	0.01 (0.01)	-0.01 – 0.03	1.00	0.02	1.01
Presence × Information Type	0.11 (0.02)	**0.07 – 0.15**	1.00	**2.28×10^{3}**	1.12
Trial Index × Information Type	0.00 (0.01)	-0.03 – 0.02	1.00	0.01	1.00
Presence × Trial Index × Information Type	0.15 (0.02)	**0.10 – 0.19**	1.00	**8.19×10^{5}**	1.16

Note. CIs = Confidence Intervals; BF = Bayes factor; IRR = Incidence Rate Ratios; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20. IRRs have been added to aid interpretation of effects. IRRs indicate how frequently an event happens in one group compared to another. Values > 1.00 indicate greater frequency and values < 1.00 indicate the opposite.

Figure 3.8

Number of Faces Viewed Per Cube Type (Experiment 2)



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error. Total viewed faces are summed and averaged for each cube type. Dashed line indicates the max number of potential faces a participant could view for each cube type.

We observed several effects within this analysis, all of which were subsumed by a three-way Presence × Trial Index × Information Type interaction. Post hoc contrasts and trend analyses were carried out to further understand this interaction.

These analyses showed that participants viewed substantially fewer faces of the poor cubes compared to the rich cubes in both target-absent trials (*Estimate* = 0.28, *lower CI* = 0.27, *upper CI* = 0.29, BF_{10} = 1.07×10^{66}) and target-present trials (*Estimate* = 0.04, *lower CI* = 0.03, *upper CI* = 0.06, BF_{10} = 84.51). This effect however was dependent on how far through the experiment a participant was. For target-absent trials, as the experiment progressed, participants decreased the number of faces viewed for poor cubes (*Estimate* = -0.08, *lower CI* = -0.10, *upper CI* = -0.06, BF_{10} = 6.94×10^{6}). In contrast, in target-present trials, as the experiment progressed, participants gradually viewed fewer cube faces for the rich cubes until there was no longer a difference between poor and rich cubes (*Estimate* = -0.07, *lower CI* = -0.09, *upper CI* = -0.04, *BF10* = 633.69).

Put simply, participants viewed ~2 less faces from the poor cubes compared to the rich cubes. However, this difference became more pronounced as the experiment progressed for target-absent trials and much less pronounced for target-present trials. This was in-line with our predictions.

3.8.7 Time to Stop Interacting Following Reveal

Finally, we examined the time it took participants to stop rotating poor cubes following stimulus reveal. Our goal here was to determine whether participants would become optimal in their searching by not continuing to interact with a poor cube following the reveal of the stimulus. As such, this analysis focused only on interactions with poor cubes where the stimulus was not visible at the start of the trial. Model effects and their corresponding CIs and Bayes factors can be found in Table 3.8 and descriptive statistics in Figure 3.9.

Table 3.8

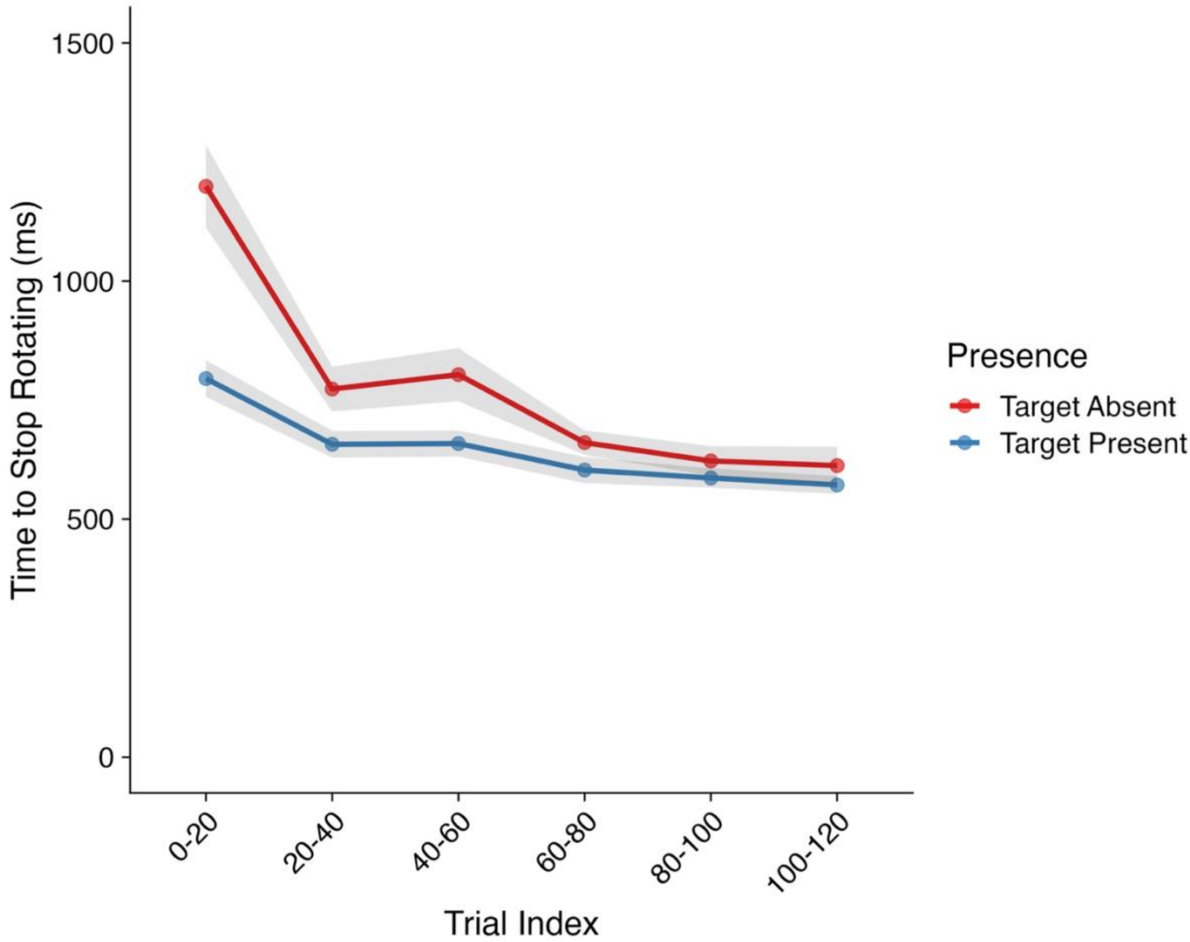
Model Effects and Bayes Factors – Time to Stop Interacting Following Reveal

Parameter	***Estimate***	***CIs***	***R-Hat***	***BF_{10}***
Intercept	6.31 (0.04)	**6.22 – 6.39**	1.00	**8.46×10^{178}**
Presence (Absent – Present)	-0.04 (0.03)	-0.11 – 0.02	1.00	0.09
Trial Index	-0.11 (0.01)	**-0.13 – -0.09**	1.00	**2.09×10^{14}**
Presence × Trial Index	0.07 (0.02)	**0.04 – 0.11**	1.00	**43.80**

Note. CIs = Confidence Intervals; BF = Bayes factor; Bolded CI values = CIs that did not pass through zero; Bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BF > 3.20.

Figure 3.9

Time to Stop Interacting Following Reveal



Note. Shaded areas represent ±SE. Trial Index has been binned into increments of 20 trials for the purposes of visualisation only. SE = standard error.

Here, we observed a Trial Index × Presence interaction which we further followed up with post hoc trend analyses. These analyses revealed that the time taken to stop interacting following stimulus reveal reduced across both target-present (*Estimate* = -0.07, *lower CI* = -0.10, *upper CI* = -0.05, BF_{10} = 5.81×10^3) and target-absent (*Estimate* = -0.15, *lower CI* = -0.17, *upper CI* = -0.13, BF_{10} = 1.04×10^{12}) trials, however, this reduction was more substantial for target-absent trials. Here, participants spent longer interacting following stimulus reveal in target-absent trials compared to target-present trials at the start of the experiment, before reducing to a similar level as target present trials.

Overall, then, it seems that participants initially were more thorough in their searching of poor cubes in target-absent trials at the start of the experiment but learned that further examining cubes where no additional information could be gained was inefficient and costly and thus was a non-optimal search strategy.

3.9 Discussion

The goal of Experiment 2 was to investigate whether varying patch values could influence attentional selection within interactive search. As with Experiment 1, we had participants conduct an interactive search for a target T shape attached to the side of a virtual cube. Within each trial, 50 % of the cubes were rich, containing six embedded shapes per cube, and the remaining 50 % were poor, containing only a single embedded shape. We found that, contradictory to our predictions, participants developed an attentional bias towards examining the poor cubes before examining the rich cubes which became stronger over the course of the experiment. However, we also found that in target-absent trials participants became less exhaustive in their searching of poor cubes – as evidenced by a reduction in faces viewed and a decrease in time taken to stop interacting following stimulus reveal – but remained exhaustive for rich cubes. This suggested that, in line with our predictions, participants learned that no additional information could be gained from revealing the remaining empty faces of the poor cubes and instead learned that their energy should be spent gathering resources from the rich cubes instead.

It was surprising to find that some of our results for Experiment 2 were misaligned with our predictions. In fact, some findings were the polar opposite of what was predicted. Fortunately, there is a simple explanation that can unify and explain the results of our two experiments in a parsimonious manner, of which we shall now turn to.

3.10 General Discussion

Interactive search is commonplace within the real world yet research into the behaviours involved within interactive search has barely scratched the surface. Across these two experiments, we have identified two new forms of attentional selection that can arise during interactive search. Our predictions for both experiments were drawn from prior research into attentional selection, the influence of physical effort on behaviours, and foraging behaviours (Anderson et al., 2025; Awh et al., 2012; Wickens, 2014; Wolfe, 2021).

For Experiment 1, we predicted that participants would examine all light cubes first and then the heavy cubes after with the aim of reducing energetic expenditure, or more simply put, physical effort. Overall, we found physical effort to be an extremely strong attribute for influencing attentional selection within interactive search. Participants consistently chose to examine the light cubes before the heavy cubes, even when doing so required travelling a greater distance. However, this increased effort was not strong enough to deter participants from still exhaustively searching through heavy cubes on target-absent trials.

For Experiment 2, we predicted that participants would examine the rich cubes first followed by the poor cubes with the aim of maximising the quantity of visual information they could obtain within any single search. However, we found the opposite; participants developed a bias towards examining the poor cubes before the rich cubes which grew stronger over the course of the experiment. Additionally, in target-absent trials, participants became less exhaustive in their searching of poor cubes but remained exhaustive for rich cubes.

This prompts an important question: Why were our predictions upheld for Experiment 1 but not for Experiment 2? We believe that a simpler explanation than first proposed can provide a clearer description of what might be occurring with respect to attentional selection during interactive searches. It is our belief that the unifying factor here across both experiments is, in fact, effort, and that what we have observed in our results is a consequence of a strategy aimed at minimising both physical and cognitive effort, and subsequently, energetic expenditure.

Let us turn to Experiment 1 to begin to explain this in detail, and we can do this by considering two simple strategies. In a *difficult-first* strategy, searchers focus on the heavy cubes followed by the light cubes; in an *easy-first* strategy, searchers focus on the light cubes first followed by the heavy cubes. On half of the trials, a target is found before all cubes are examined: in fact, on average, with four cubes per trial, a target will be found by the time that two cubes have been examined in a trial. Of course, once a target has been found, the trial ends and no more cubes are examined. Should a searcher engage in a difficult-first strategy, they will expend the highest possible amount of energy and effort per cube before finding the target; but should a searcher engage in an easy-first strategy, they will expend very little energy and effort in comparison before finding the target. It therefore makes sense that searchers focused on an easy-first strategy in Experiment 1: doing so enabled them to conserve their effort and energy to a substantial degree.

The same argument can be used to re-cast and explain the results of Experiment 2, which were contrary to our predictions. If one does not know where a target may appear, then focusing on areas with the largest number of potential targets would be a more efficient strategy than focusing on areas with only a small number of potential targets. Thus, participants in our task were engaging in a non-optimal strategy. However, if effort is taken into consideration, then the costs of examining the rich and poor cubes becomes important. With many more objects to examine, the rich cubes ultimately would have required more energetic expenditure and processing time than the poor cubes to fully examine. There are several reasons for this perceived increase in cognitive effort, however, a particularly prominent reason is the increase in the number objects a participant must hold in working memory whilst searching through a rich cube compared to a poor cube. Here, instead of simply being able to check whether a face is empty or contains a shape, participants instead need to keep track of which of the six faces have been seen and whether each face contained a T or an L shape. Additionally, this increase in visual information, perceptual load, and perceptual difficulty further escalates the risk that a participant may reveal and un-reveal the target face without realising (e.g., Solman et al., 2012). Thus, when considering the effort involved in search, a difficult-first strategy for Experiment 2, would involve examining all rich cubes before poor cubes; and an easy-first strategy for Experiment 2, would instead involve examining all poor cubes before rich cubes. Clearly, then, the search system is prioritising effort and energetic expenditure when selecting candidate objects for detailed inspection during interactive search and overruling other considerations such as the quantity of resources a patch contains or the perceived probability that a given cube would contain a target object.

Overall, then, our two experiments combined highlight that, during interactive search, searchers, adopt an 'easy-first' strategy, focusing on objects that can be rapidly, easily, or with little effort, rejected as distractors or accepted as containing a target. In fact, though counterintuitive in some regards, our findings neatly dovetail with those reported in studies of visual search. Across a number of visual search studies, participants have been shown to use sub-optimal search strategies in an attempt to reduce perceived cognitive effort (Irons & Leber, 2016, 2018; T. Zhang & Leber, 2024). As noted above, to our knowledge this is the first set of experiments that have been conducted with the aim of better understanding attentional selection during interactive search, and we have generated a novel set of findings regarding prioritisation during interactive searches. At a theoretical level, these findings can help to better understand how, when and why regions are examined during interactive search.

It is, however, important to note that our findings may be driven not by a focus on 'easy' objects first, but rather by a focus on those objects that can be examined quickly. Under this view, the longer a participant spends examining an object, the more energy and resources they must expend doing so. By prioritising objects that can be accepted or rejected quickly, e.g., light and poor cubes, participants may therefore have been focused on reducing energetic expenditure by being more efficient with their time[1]. Here, we did not plan on controlling for this possibility, and so drawing conclusions in this regard is beyond the scope of the current set of

[1] We thank two anonymous reviewers for raising this possibility to us.

experiments. However, we plan on pursuing this in future research wherein the time taken to examine objects is held constant.

At a practical level, our findings also bear importance on interactive search tasks. Whether in the digital or physical world, we expect searchers to de-prioritise interactively examining objects that indicate in some way that they will require extensive effort to search. Doing so could cause these objects to not be examined at all should a searcher be under time pressure and thus terminating their searches rapidly. In our simple interactive search tasks here, performance was high and the cubes that needed more effort did not show evidence of targets being missed. However, it may be the case that in interactive search tasks that require substantially more effort overall, such as when searching for targets hidden throughout a house (Riggs et al., 2018), individuals may become more likely to avoid these objects altogether. This is indeed a possibility that we plan to examine within future experiments.

Chapter 4 What Drives Object Selection? The Combined Role of Temporal Costs and Effort during Interactive Search

Notes

This chapter is an empirical paper which is currently under review at the *Quarterly Journal of Psychology*.

Authors: Haden Dewis, Cheryl D. Metcalf, Martin B. Warner, Richard Polfreman, & Hayward J. Godwin

CRediT (Contributor Roles Taxonomy)

Dewis: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, validation, writing – original draft preparation. Godwin: Conceptualization, investigation, methodology, project administration, resources, software, supervision, validation, writing – review & editing. Metcalf: writing – review & editing, supervision. Warner: writing – review & editing, supervision. Polfreman: writing – review & editing, supervision.

Open Practice Statement

The raw trial data for both experiments, the final processed datasets, and all associated code used for processing and analysing the data is freely available on the Open Science Framework at https://osf.io/ajy9t/.

Abstract

In a prior set of experiments, we examined drivers of attentional selection within interactive search, specifically focusing on the role of effort (Dewis et al., 2025). We concluded that searchers adopted an easy-first strategy, prioritising selections with easy to process objects. However, we unintentionally overlooked the potential confound of time within these tasks and consequently, our analyses and conclusions. We have addressed this in the current manuscript by carefully controlling for and further exploring the role of time within interactive search. We utilised a novel methodology which involved effortful interactive search for a target T shape attached to the underside of a set of virtual coins across two independent experiments. In Experiment 1, we manipulated effort whilst controlling for the confound of time. In Experiment 2, to obtain a richer understanding of the role of time within effortful interactive search, we manipulated both time and effort simultaneously. We observed a surprising set of results: first, effort appears to be the predominant driving factor of attentional selection across our tasks, and second time is indeed an aversive attribute to attentional selection, especially so when paired with high effort, i.e., high effort tasks that also take substantial time to complete. The implications of these results are discussed within the manuscript.

Keywords: Interactive Search, Visual Search, Guided Search, Effort

4.1 Introduction

Many tasks in everyday life require direct interaction with our environment and the objects within it. One of the more common day-to-day tasks that requires this is search. For example, searching through a bag for a phone, searching kitchen cupboards for ingredients, or searching through an office drawer for a pen. These are all examples of *interactive search tasks*, a term coined by Sauter et al. (2020). Interactive search is an extension of visual search (for a review, see Wolfe, 2020) and involves scenarios wherein a searcher sets out to detect a target, or confirm its absence, through the uncovering of obscured visual information via object manipulation or via translation of their own physical position within the environment. Several studies have examined interactive search across a range of contexts including simple tasks such as searching through marbles, LEGO® pieces, and simple blocks for targets (Gilchrist et al., 2001; Hout et al., 2022; Sauter et al., 2020) to more real-world tasks including searching through open terrain for target objects (Riggs et al., 2017) or entire houses for threats (Riggs et al., 2018). Likewise, interactive search is not limited to just the physical domain and has been assessed across a number of virtual domains as well. Typically, this has involved searchers using external peripherals to manipulate virtual objects (Dewis et al., 2025; Solman et al., 2012) or to change virtual displays (Drew et al., 2013; Godwin et al., 2024; Solman et al., 2013). In the current paper, we build on this existing literature via the examination of behaviours within a set of virtual interactive search tasks.

The starting point for the current project is a series of prior experiments where we examined the factors that drive attentional selection within interactive search, specifically focusing on the role of effort (Dewis et al., 2025). From a visual standpoint, attentional selection refers to the deployment of attention to relevant objects and areas of a scene due to the inability to process all objects within a scene at once (Wolfe, 2021). Many current models characterise this complex deployment of attention as being driven by a "priority map" populated from numerous factors including top-down (the current goals of the searcher – e.g., searching for an object of specific colour) and bottom-up (the physical salience of a stimulus – e.g., a bright object amongst dull objects) inputs (Corbetta & Shulman, 2002; Itti & Koch, 2000b; Wolfe, 1994b), selection history and priming (Awh et al., 2012; Maljkovic & Nakayama, 1994), perceived reward (Anderson et al., 2011; Hickey et al., 2010b, 2010a, 2015), semantic knowledge (Henderson & Hayes, 2017; Le-Hoa Võ & Wolfe, 2015; Pedziwiatr et al., 2021; Võ et al., 2016; Võ & Wolfe, 2013; Wolfe et al., 2011), and potentially many others factors (Godwin et al., 2014; Wolfe, 2021; Wolfe & Horowitz, 2017).

Although there is a body of work looking at the effects of effort upon simple visual search tasks (e.g., Anderson & Lee, 2023), beyond our previous work (Dewis et al., 2025), we are not aware of any prior research examining effort in the context of virtual interactive search. With this in mind, in Dewis et al. (2025), we reported that participants adopted what we termed as an 'easy-first' strategy when engaged in interactive search. This conclusion was drawn from two experiments wherein participants searched for target T shapes amongst distractor L shapes that were embedded onto the sides of a set of virtual cubes. Participants rotated and interacted with the virtual cubes by clicking and dragging on them with their computer mouse. In Experiment 1, we manipulated physical effort. Here, half of the cubes within each trial were made to be physically effortful to rotate by reducing their sensitivity to mouse inputs in comparison to the remaining cubes. In Experiment 2, we manipulated the quantity of shapes attached to the side of cubes – a proxy for "patch value" – the perceived value assigned to different areas containing resources (e.g., Charnov, 1976). Within each trial, half of the cubes were made to be "information-rich" (e.g., Nahari & El Hady, 2025) by embedding a shape onto each face of the cube, and the remaining half were made to be "information-poor" by embedding a single shape onto only one of their six possible faces. Across both experiments, cube types could be differentiated by their colours: this enabled participants to identify cube types without needing to physically interact with them first.

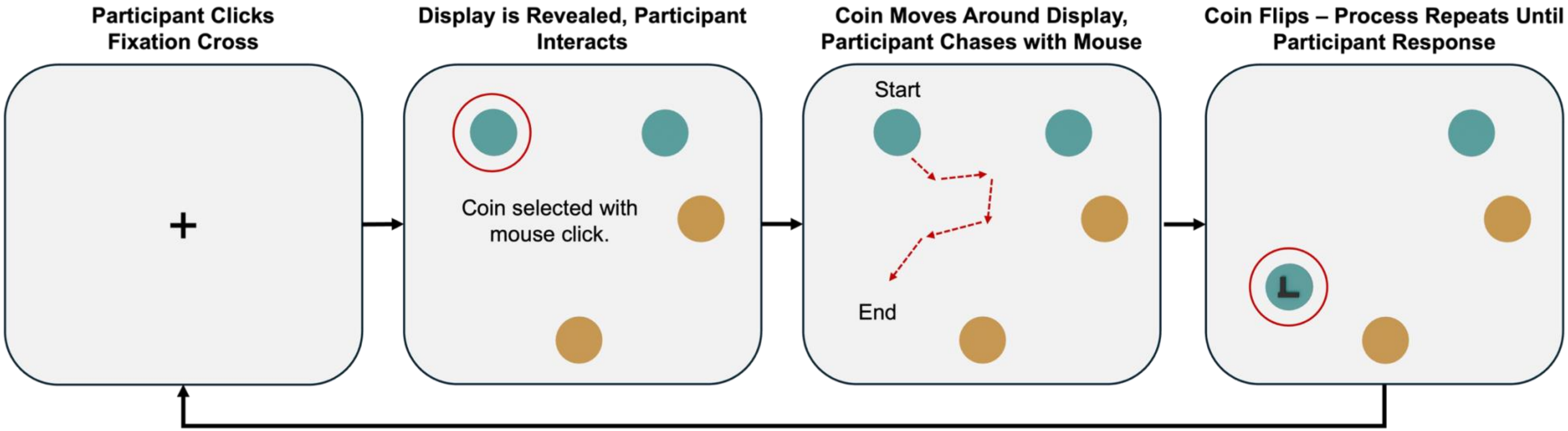
Overall, participants showed an extremely strong bias towards prioritising cubes that were physically easy to rotate (Experiment 1) and easy to process (Experiment 2). Based upon these results, as noted above, we concluded that searchers adopted an easy-first strategy, focusing on objects that could be rapidly, easily, or with little effort, rejected as distractors or accepted as containing a target. However, during the peer-review process, two anonymous reviewers raised the concern that our experiments had a potential confound: both the high effort and information-rich cubes in our experiments not only required more effort to examine, but more time to examine as well. Perhaps, the reviewers argued, our results were due to the search system prioritising objects that could be searched more rapidly, than with less effort. From a resource standpoint, effortful tasks require energy to conduct. This increase in consumption of resources is likely one of the potential reasons high effort tasks are so aversive. If we also consider the time a task takes to be an indication of the potential consumption of these resources, then engaging in strategies to reduce the time taken to complete tasks seems very logical indeed. Conducting research on effortful tasks whilst overlooking the role of time is therefore a valid concern. However, doing so was beyond the scope and design of the experiments reported by Dewis et al. (2025). It was not possible for high effort cubes to rotate at the same speed as low effort cubes in Experiment 1 as speed was used to influence their perceived effort; likewise, in Experiment 2, it was not possible to have information-rich cubes be explored exhaustively within the same time frame as information-poor cubes as interacting to reveal six shapes versus one would always take longer to achieve. Put simply, we overlooked the potential effects of time both in terms of our design and, as a consequence, our analyses and conclusions.

4.1.1 Current Experiments

Given the potential confound of time that we previously overlooked, within the current project we returned to the question of effort being a driver of attentional selection whilst both accounting for, and further exploring, the effects of time. To do so, across two experiments, we asked participants to complete a virtual interactive search task for a target T shape amongst distractor L shapes, both of which were attached to the undersides of a set of four virtual coins. To reveal the hidden shapes, participants had to “flip” coins by clicking on them with their computer cursor. However, to ensure effortful interaction, following the initial selection, the coin moved around the display, requiring participants to chase it with their cursor before it flipped over, see Figure 4.1. A video of the task can also be found at this link: https://osf.io/56my7. In Experiment 1, we ensured the time taken to interact remained constant between all coins. In Experiment 2, however, we further investigated the role of time by varying the time required to interact with certain coins. The decision to change to coins over cubes was a deliberate one. Within our previous methodology, increases in effort resulted in increases in interaction time: high effort cubes required more time to rotate as they rotated at a slower rate than low effort cubes. Switching to coins that moved erratically around the screen allowed for a way to increase and maintain effort whilst carefully controlling for time. Here, effort could be manipulated by the erratic nature of the coin movement and time controlled for by manipulating the total duration of coin movement; something that was not possible with the previous methodology. By doing so, we were able to shed light on whether Dewis et al. (2025) were correct in their conclusions despite overlooking the role of time.

Figure 4.1

Basic Trial Procedure for Experiments 1 and 2



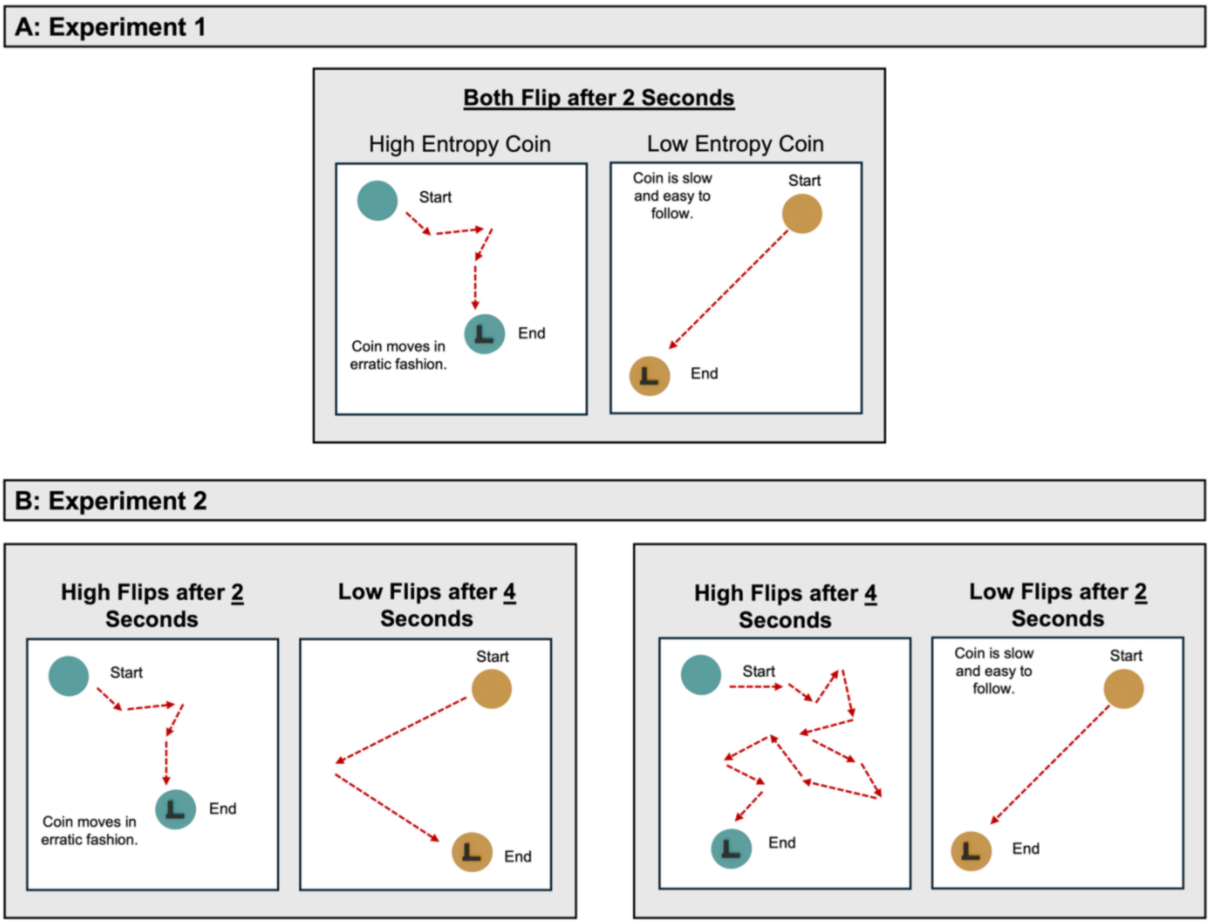
Note. Figure depicts a standard trial for both Experiment 1 and Experiment 2. The red circles and arrows were not visible to the participant and are included here to aid visibility. Participants used their cursor to click on a fixation cross presented in the middle of the screen to start a trial (first panel). The display was then revealed, and participants selected a coin to interact with using their cursor (second panel). Following the selection, the coin moved around the display whilst the participant chased it with their cursor (third panel). After a period of continuous chasing, the selected coin flipped over to reveal the attached T or L shape (fourth panel). The participant would then either select a new coin or end the trial with a keyboard press. This whole process repeated for 120 trials.

4.2 Experiment 1

In Experiment 1, we began by investigating the role of effort within interactive search whilst carefully controlling for the potential confound of time spent interacting. As previously stated, participants were presented with a set of four virtual coins that required chasing and flipping to reveal a hidden T or L shape attached to their underside (see Figure 4.1). We specifically manipulated the effort required to interact with coins and have depicted this manipulation within the top panel of Figure 4.2. Here, two of the four coins within each trial moved around the display in a quick and unpredictable manner, frequently changing directions, making them require both substantial cognitive and physical effort to track and chase around the display. In contrast, the remaining two coins moved in a slow and predictable manner, making them much easier to track and interact with (i.e., required a low level of effort). Hereafter, we will refer to these coin types as *low entropy* and *high entropy* coins. To ensure the confound of time was controlled for, each coin only required chasing for a total of two seconds before flipping over. Colour was used to provide a means of differentiation between the coins to ensure participants could identify coin types without needing to physically interact with them first.

Figure 4.2

Experiment Manipulation Illustration



Note. Figure depicts effort and time manipulations for both experiments. Upper panel depicts effort manipulation for Experiment 1 only. Lower panel depicts effort and time group manipulation for Experiment 2. The red circles and arrows were not visible to the participant and are included here to aid visibility

If, as previously suggested by Dewis et al. (2025), effort is indeed an attribute that influences interactive search, then, within our experiment, we expected that whilst time was held constant, our effort manipulation should still influence attentional selection. As such, we predicted that the influence of effort would manifest itself as an increase in bias towards selecting the low entropy coins, even when they were not the next closest object to their current position. Furthermore, due to the low effort of doing so, we predicted that we would observe an overall increase in the number of low entropy coins flipped.

4.3 Method

4.3.1 Open Materials and Data Availability

This study was not pre-registered. We have shared the raw by-trial data and all analytic code on the Open Science Framework: https://osf.io/ajy9t/.

4.3.2 Ethical Approval

Ethical approval was given for Experiment 1 by the University of Southampton's Ethics Committee on the 13th of March 2025 (ERGO NUMBER: 95398.A2).

4.3.3 Participants

A priori power analyses were conducted using the *SIMR* packing in R (P. Green & MacLeod, 2016; R Core Team, 2023) on pilot data from 15 participants. Power analyses were conducted for the first dependent variable being analysed. Target effect sizes were loosely informed by prior research (Dewis et al., 2025; Godwin et al., 2024). These analyses recommended a minimum sample size of ~35 participants to achieve a power level of 0.80 for an effect size of 0.15. We over-recruited to a small extent a total of 38 participants from the University of Southampton (Age: M = 19.67, SD = 1.42, Gender: Female = 84.62 %, Male = 15.38 %) throughout March to May 2025 of whom received course credit for their participation.

4.3.4 Stimuli and Apparatus

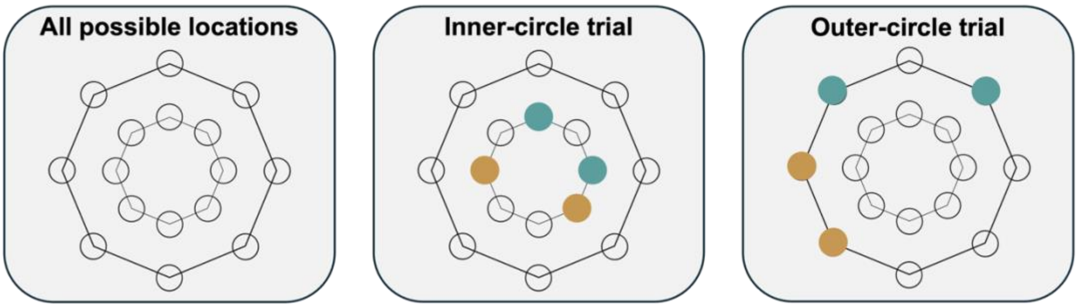
Stimuli were created using the open-source software Blender (Hess, 2010). Virtual displays that contained these stimuli were then generated using Three.js (an open-source JavaScript library for displaying three-dimensional graphics within web browsers; Danchilla, 2012) and embedded into a standard jsPsych framework (an open-source JavaScript library for building web-based psychological experiments; De Leeuw, 2015).

The stimuli for Experiment 1 consisted of four different types of virtual coins with shapes attached to their undersides: low and high entropy coins with a distractor L shape attached, and low and high entropy coins with an attached target T shape instead. Coins were assigned a single independent colour at the start of the experiment which did not change throughout. This was to ensure that participants could easily differentiate between low and high entropy coin types. Coin colours were selected from a list of 16 ordered colours used in previous visual and interactive search experiments (e.g., Dewis et al., 2025; Menneer et al., 2007; Stroud et al., 2012). Each consecutive colour was approximately equally spaced from the previous in CIE xyY space. To reduce the risk of biases towards specific colours, the colour chosen for high entropy coins was always randomised at the start of the experiment. To ensure that colours were then maximally different from each other, the colour selected for the low entropy coins was always eight steps away from the previous selected colour in the list. The attached T and L shapes were black to ensure they were easily visible across the whole range of colours.

For each trial, the search display consisted of two low entropy and two high entropy coins which were randomly assigned to one of eight possible locations within the display. As shown in Figure 4.3, coins were placed within one of two concentric circles (inner or outer) each of which contained eight equidistant locations from the centre of the display. A single trial could not contain coins in both the inner and outer circles simultaneously. Our reason for doing so was to reduce any biases that may result in participants simply selecting the coin closest to the centre of the display. Fifty percent of trials were inner circle trials and 50% were outer-circle trials.

Figure 4.3

Coin Placing Procedure



Note. Figure depicts all the possible locations that coins could have been placed for each trial. The outlines of the circles and locations were not visible to the participant.

Participants used their own computers or laptops to complete the experiment. They were informed to press the M key of their keyboard if they believed that the display contained a target shape and the Z key if they believed that it did not. Participants interacted with objects by clicking on them with their computer mouse.

4.3.5 Design and Procedure

Following consent, participants were provided with detailed instructions on what to expect within the experiment, and how to interact with the coins. Participants were then given the chance to complete five practice trials with accuracy feedback before beginning the real trials which contained no feedback. Each participant completed a total of 120 interactive search trials. To ensure participants began each trial with their cursor at the centre of the display, a central fixation cross had to be clicked with the mouse before each trial's search display was revealed. The search display remained visible until a response was made by the participant to end the trial. Following the participant response, the next trial's fixation cross was displayed and all steps then repeated for 120 trials. This process is depicted in Figure 4.1.

The target was present on 50 % of search trials and absent for the remaining 50 %. Stimuli were evenly split between high and low entropy coin types. The order in which participants completed trials was randomised. The same colour contingencies were used during the practice trials as were during the real trials.

4.4 Results

4.4.1 Data Cleaning

Before beginning analysis, all data underwent a number of preplanned cleaning procedures as used in previous online visual and interactive search experiments (Dewis et al., 2025; Godwin et al., 2024; Godwin & Hout, 2023). A breakdown of the number of trials removed for Experiment 1 can be found in Table 4.1.

The data cleaning process involved three distinct steps. In step one, we removed trials where participants had not flipped the coin containing the target yet still responded that the target was present. In such a scenario, if the target was never revealed, then participants had no way of knowing whether the target was present and therefore had to have been guessing on these trials, thus making them invalid. In step two, we removed any trials whose response times were shorter than 250 ms. This criterion was decided upon since chasing and revealing any single coin would have taken ~2 seconds. As such, it is implausible that a participant could have revealed a coin and responded within such a short time frame. Finally, in step three, we removed any trials where participants took longer than 60 seconds to respond. Likewise, we determined this value to be a reasonable time for participants to have interacted with each of the four coins within a trial.

Following all cleaning procedures, the final dataset for Experiment 1 consisted of 4,519 (99.09 %) trials from 38 participants.

Table 4.1

Data Cleaning Steps for Each Experiment

	Experiment 1		Experiment 2	
Removal Step	**Trials Removed**	**Remaining Trials**	**Trials Removed**	**Remaining Trials**
Raw Data	0 (0.00 %)	4,560 (100.00 %)	0 (0.00 %)	4,800 (100 %)
Guessing Trials	13 (0.29 %)	4,547 (99.71 %)	48 (1.00 %)	4,752 (99.00 %)
Fast Trials	8 (0.18 %)	4,539 (99.53 %)	0 (0.00 %)	4,752 (99.00 %)
Slow Trials	20 (0.44 %)	4,519 (99.09 %)	15 (0.31 %)	4,737 (98.69 %)

Note. "Guessing Trials" refers to target-present trials in which participants responded present yet never flipped over the coin containing the target. Fast trials = trial response times < 250 ms; Slow Trials = trial response times > 60,000 ms for Experiment 1 and > 120,000 ms for Experiment 2.

No participants were removed from any datasets.

4.4.2 Analytic Approach

In this study we modelled regression coefficients using Bayesian generalised linear mixed-effects models (BGLMMs) via the *brms* package in R (Bürkner, 2017b). The reliability of these effects were confirmed using Bayes factors (BFs), calculated via the *bayestestR* package in R (Makowski et al., 2019). Bayes factors are a likelihood ratio test between the null hypothesis and an alternative hypothesis. Bayes factors larger than 1.00 suggest stronger evidence towards the alternative hypothesis and values smaller than 1.00 suggest stronger evidence towards the null hypothesis. As such, unlike within traditional null-hypothesis testing, BFs provide a means of interpretation for null effects. For the purpose of our discussion, we have deemed an effect to be trustworthy when both its 95% credible interval (CI) did not pass through zero and its BF was larger than 3.20.

Where relevant, models used the following fixed factors: Coin Type (high entropy, low entropy) and Presence (target-absent, target-present). All models included random intercepts for Participant ID. This allowed for the small random variations between participants to be accounted for when modelling effects. Models that did not use a full random structure did so due to model fitting errors. When models with full random structure returned fitting errors, the random structures were trimmed from the model until model fitting errors no longer occurred. As within the previous chapters, flat priors were chosen for all analyses due to the novel and exploratory nature of the study and associated analysis.

The study utilised three dependent variables. The first was the likelihood of selecting either of the two coin types. This was measured using a binary variable where 1 indicated that the first interaction of a trial was made to this coin type and 0 indicated that it was not. The second was the overall likelihood that a participant would select either of the two coin types as their second interaction. Again, this was coded as a binary variable with 1 representing that the second interaction of a trial was made to this coin type and 0 indicated that it was not. These analyses focused only on participants' first and second interactions. Our reason for doing so was that participants' third and fourth interactions were typically a mirror of their first and second interactions; as was also the case for Dewis et al. (2025). For example, if a participant's first two interactions were to the low entropy coins, then their remaining interactions would be to the two outstanding high entropy coins and vice versa. Finally, our third dependent variable was the number of coins flipped. This was measured as a count between 0 and 4 across each trial. We used relatively flat priors (M = 0.00, SD = 1.00) for all analyses, employed a Bernoulli distribution with a logit link when modelling binary variables, and a Poisson distribution when modelling the total number of coins flipped. Each model was fitted using four chains, with

11,000 iterations and 1000 warmup iterations. All Gelman-Rubin statistics were below 1.10 for all parameters and visual inspection of the chains indicated good mixing.

4.4.3 Response Accuracy and Response Times

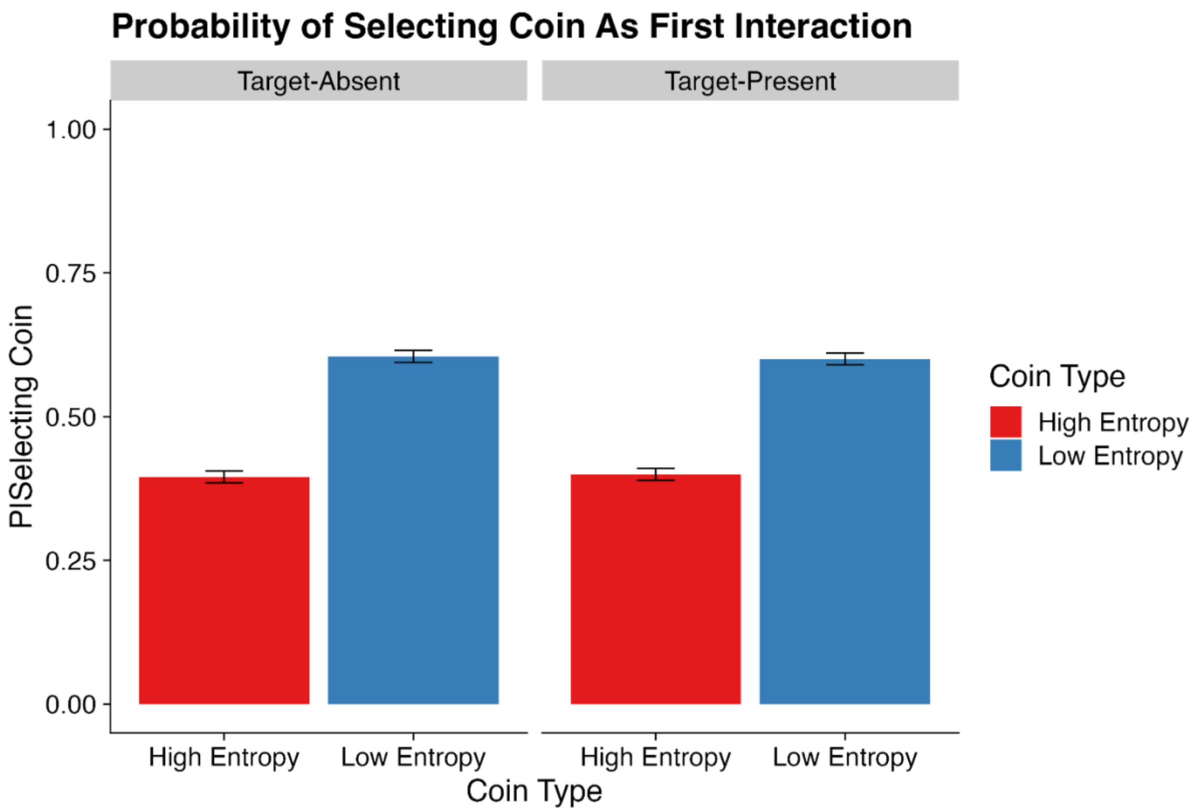
Overall, response accuracy was high for both target-present (*M* = 0.98, *SD* = 0.15) and target-absent trials (*M* = 0.99, *SD* = 0.11). Likewise, participants completed trials within a reasonable time for target-present (*M* = 10,929.35 ms, *SD* = 6,440.27 ms) and target-absent trials (*M* = 16,691.92 ms, *SD* = 6,842.90 ms). No further analyses were conducted on response accuracy or response times. Our remaining analyses focused on the order of interactions and the number of coins flipped.

4.4.4 First Coin Selected

We began by focusing on the first coin participants selected across each trial as a function of Coin Type. Descriptive statistics can be found in Figure 4.4 and model effects and BFs are within Table 4.2. Within this analysis we uncovered a main effect of Coin Type on first selection choice. Here, participants were, on average, more likely to select a low entropy coin as their first interaction than they were a high entropy coin. Overall, then, when time was held constant, effort still appeared to be a factor that influenced initial object selections within interactive search. This was in line with our predictions.

Figure 4.4

Descriptive Statistics for Analysis 1, Experiment 1 – Probability of Selecting Coin



Note. Errors bars = ± standard error.

Table 4.2

Model effects and Bayes factors for All Analyses – Experiment 1

	Parameter	*Estimate*	*CIs*	*R-Hat*	*BF_{10}*	*OR/IRR*
(A): Analysis 1	Intercept	0.00 (0.02)	-0.04 – 0.04	1.00	0.01	1.00
	Coin Type (High Entropy, Low Entropy)	-0.83 (0.04)	**-0.91 – -0.75**	1.00	**2.05×10^{23}**	0.44
(B): Analysis 2	Intercept	-0.00 (0.03)	-0.05 – 0.05	1.00	0.01	1.00
	Coin Type (High Entropy, Low Entropy)	-1.24 (0.05)	**-1.35 – 1.14**		**1.19×10^{30}**	0.29
	Nearest Coin Type (High Entropy, Low Entropy)	0.00 (0.05)	-0.11 – 0.11	1.00	0.05	1.00
	Coin Type × Nearest Coin Type	1.73 (0.11)	**1.52 – 1.94**	1.00	**2.71×10^{16}**	5.65
(C): Analysis 3	Intercept	0.37 (0.02)	**0.33 – 0.40**	1.00	**5.29×10^{20}**	1.44
	Presence (Target-Absent, Target-Present)	-0.60 (0.02)	**-0.63 – -0.56**	1.00	**1.44×10^{38}**	0.55
	Coin Type (High Entropy, Low Entropy)	-0.11 (0.02)	**-0.15 – -0.08**	1.00	**1.44×10^{4}**	0.89
	Presence × Coin Type	-0.17 (0.04)	**-0.25 – -0.10**	1.00	**742.29**	0.84

Note. CIs = Credible Intervals; BF = Bayes Factor; OR = Odds Ratios; IRR = Incidence Rate Ratios; bolded CI values = CIs that did not pass through zero; bolded BF values = BF > 3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BFs > 3.20.

(A): Analysis 1 = Probability of Selecting Coin as First Interaction.

(B): Analysis 2 = Probability of Selecting Coin as Second Interaction.

(C): Analysis 3 = Total Coins Flipped.

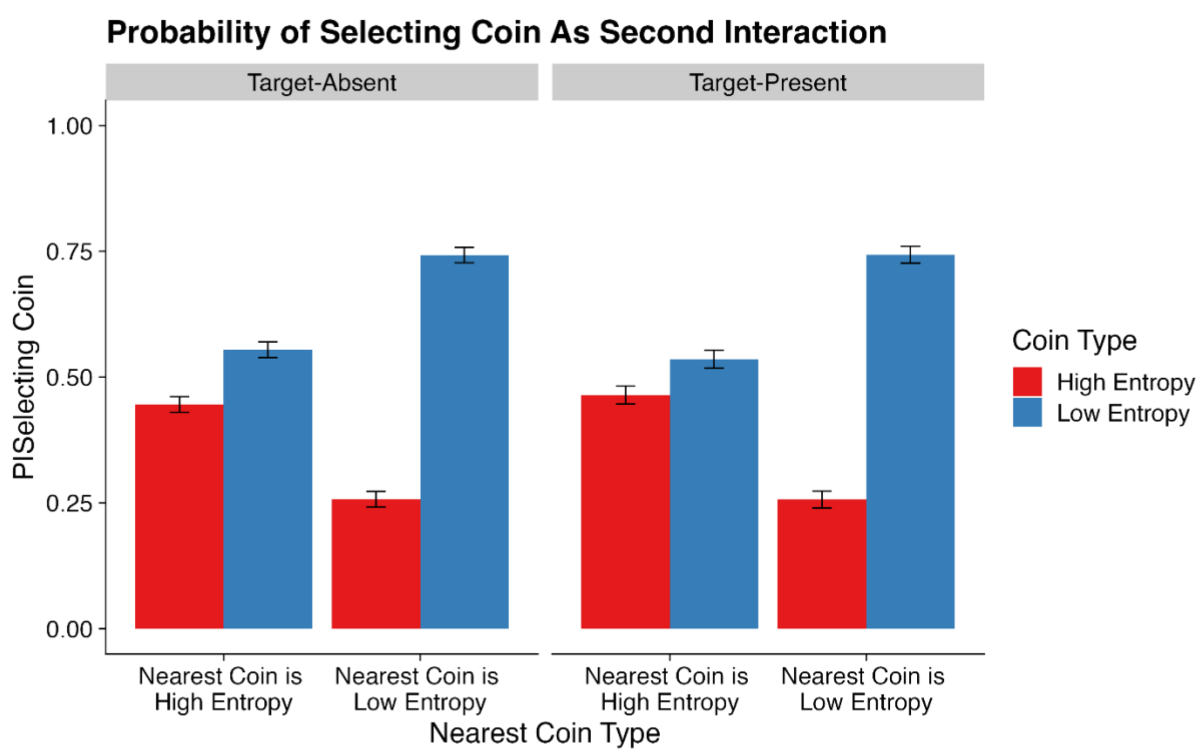
ORs and IRRs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite. IRRs are used for count data and indicate how frequently an event happens in one group compared to another. Values > 1.00 indicate greater frequency and values < 1.00 indicate the opposite.

4.4.5 Second Coin Selection

At the start of each trial, participants clicked on a central fixation cross to reveal the display. As such, this is where their attention should have been focused (e.g., Anwyl-Irvine et al., 2021). We have shown above that when all coins were equidistant from the centre, participants had a tendency to focus their attention towards low entropy coins as their first selections. But was this still the case for their second selection, i.e., once the remaining coins were no longer equidistant from the participant's current cursor position? We addressed this by examining the likelihood that participants would select a specific coin as their second interaction with an additional model factor that measured whether the nearest coin was low or high in entropy. By doing so we were able to account for the role of coin distance within participants' selection choices. As a reminder, should effort still have been a driver of attentional selection, then we expected an overall high likelihood that participants would select low entropy coins as their second selection, and an increase in this bias when the nearest coin to their current position was also low in entropy. Descriptive statistics can be found in Figure 4.5 and model effects and BFs within Table 4.2.

Figure 4.5

Descriptive Statistics for Analysis 2, Experiment 1 – Probability of Selecting Coin Second



Note. Errors bars = ± standard error.

Within this analysis we first observed a main effect of Coin Type. This suggested that participants predominantly opted to select low entropy coins as their second selection. Following this, we observed an interaction between Coin Type and Nearest Coin Type. We conducted several post-hoc contrasts which showed that participants were more likely to select a low entropy coin over a high entropy coin both when the nearest coin was high (*Estimate* = 0.38, *lower CI* = 0.24, *upper CI* = 0.50, BF_{10} = 1.32×10^{4}) and when it was low (*Estimate* = 2.11, *lower CI* = 1.94, *upper CI* = 2.27, BF_{10} = 1.47×10^{28}). However, this effect was substantially stronger when the nearest coin was low.

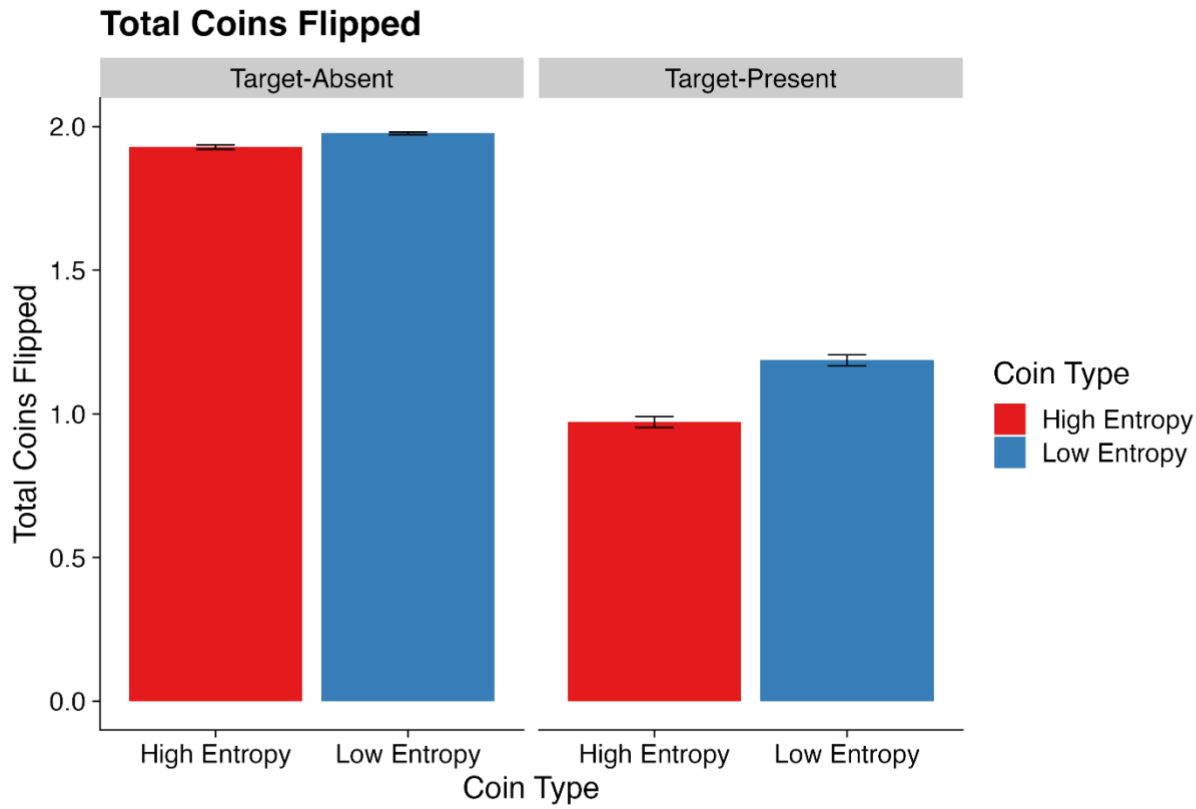
Overall, our findings confirmed our predictions. As was the case for their first selection, participants also showed a bias towards selecting low entropy coins second. Furthermore, as predicted, this effect was amplified when the nearest coin was also low in entropy. Our findings further showed that participants were often willing (~54 % of the time) to travel the extra distance to low entropy coins even when they were not the nearest coin. Conversely, participants rarely did this for high entropy coins (~25 % of the time). Again, this was in line with our predictions. However, it is important to note that when the nearest coin was high in entropy, coin selection became more varied, with participants opting to select the high entropy coin ~45 % of the time despite the associated increase in effort. As such, this implied that our effect may not have been as strong as was observed within Dewis et al. (2025) and that for second selections, closest coin type sometimes played a role. This was not directly in line with our predictions.

4.4.6 Total Coins Flipped

Our final analysis focused on search exhaustiveness, as measured by the number of coins flipped. Descriptive statistics can be found in Figure 4.6, and model effects and BFs within Table 4.2.

Figure 4.6

Descriptive Statistics for Analysis 3, Experiment 1 – Total Coins Flipped



Note. Errors bars = ± standard error.

Within this analysis, we found main effects for both Presence and Coin Type, both of which were subsumed by a Presence × Coin Type interaction. Post-hoc contrasts were conducted to better understand the relationship of this interaction. Here, when controlling for coin type, participants flipped a greater number of coins in target-absent trials than they did target-present trials, for both low entropy coins (*Estimate* = 0.51, *lower CI* = 0.46, *upper CI* = 0.56, $BF_{10} = 2.38 \times 10^{22}$) and high entropy coins (*Estimate* = 0.69, *lower CI* = 0.63, *upper CI* = 0.74, $BF_{10} = 1.08 \times 10^{36}$). However, when controlling for target presence, participants flipped a greater number of low entropy coins than they did high entropy coins within target-present trials (*Estimate* = 0.20, *lower CI* = 0.14, *upper CI* = 0.26, $BF_{10} = 1.76 \times 10^{5}$) but not within target-absent trials (*Estimate* = 0.02, *lower CI* = -0.02, *upper CI* = 0.06, BF_{10} = 0.04).

To summarise, participants flipped more low entropy coins than they did high entropy coins but only within target-present trials. The reason for this interaction can be explained by a bias towards low entropy coins. Here, in target-present trials, the target should predominately be found without needing to uncover all four coins. As a clarification, from a probabilistic standpoint, when a target is placed randomly amongst four items and those items are checked in a serial fashion, the likelihood of uncovering that target should be a uniform distribution. As such, if participants were predominately selecting low entropy coins, then they would have flipped more of these coins in trials where interacting with all four coins was not always necessary. This was in line with our predictions.

4.5 Discussion

In Experiment 1, we addressed the potential confound of time within effortful interactive search; a key factor that was as unaccounted for within our previous research into effort and interactive search (Dewis et al., 2025). To do so, we asked participants to engage in an interactive search task for a target T shape attached to the underside of a virtual coin. Coins were interacted with by using a computer mouse to click on them. Following an initial selection, the coin moved around the display. Participants chased the coin around the display with their cursor continually clicking the coin. After two seconds of continuous chasing, the coin flipped over to reveal the obscured information. On each trial, two of the four potential coins moved in a quick and unpredictable manner (i.e., required more effort) whilst the remaining two moved in a slow and predictable fashion (i.e., required less effort). Based on the prior research by Dewis et al. (2025), we therefore predicted that participants would prioritise the selection of coins that required the least physical and cognitive effort to interact with.

When holding time constant, participants still prioritised low effort objects over high effort objects (i.e., low entropy versus high entropy). We observed this within the first and second selections participants made across each trial. These findings were in line with our predictions. However, it is important to note that the results of our second analysis also indicated that the bias towards low entropy coins was weaker when low entropy coins required travelling a greater distance to select. As such, this suggests that the effect of effort observed here was not as strong as it was for the prior experiments conducted by Dewis et al. (2025). Finally, we further predicted that participants would flip more low entropy coins compared to high entropy coins. This was indeed an effect of which we observed but only for target-present trials. This was unsurprising however, since search exhaustiveness of target-absent trials have typically remained high within interactive searches, despite increases in effort (Dewis et al., 2025).

These findings provide valuable insights into the roles of effort and time within attentional selection. Primarily, when time is held constant, effort is still an aversive attribute that influences attentional selection within interactive search tasks, albeit not as strong as previously observed. Perhaps then, when effort is involved, time does indeed play an important role within the biasing of attentional selection for interactive search. Should this be the case, then determining which of the two is the primary driver of attentional selection within aversive effortful tasks is paramount. We addressed this within Experiment 2.

4.6 Experiment 2

Following our findings from Experiment 1, we conducted an additional study further investigating the interaction between effort and time, directly addressing the issue of how these two factors combine. We used the same approach as Experiment 1, wherein participants chased coins around the display, continually clicking them to flip them over. As before, effort was varied between coins. However, as we have illustrated within the bottom panel of Figure 4.2, we included an additional time manipulation into the paradigm wherein some coins required chasing for longer before flipping over. Here, participants were placed into one of two time conditions. In the "Low Entropy Flipped Sooner" condition, the low entropy coins flipped over after two seconds of chasing and the high entropy coins flipped over after four seconds of chasing. In the "High Entropy Flipped Sooner" condition, the high entropy coins flipped after two seconds of chasing and the low entropy coins flipped after four seconds of chasing. Here, our goal was to better understand which of the two, between time and effort, was the predominant driving factor for attentional selection biases within our interactive search task.

As previously discussed, should participants prioritise objects that can be searched quickly, then an interaction should arise between our time and effort manipulation. Hence, we predicted that participants would become more biased towards low entropy coins, but only when they also flipped sooner. Likewise, when the high entropy coins flipped sooner, then regardless of the effort involved, we predicted that participants would be more likely to be biased towards these coins instead. As with the previous experiment, we predicted that this would be evident within participants' first and second selections across each trial, and the total number of coins flipped for each coin type.

4.7 Method

All methodological details for Experiment 2 were identical to Experiment 1, except where described below.

4.7.1 Ethical Approval

Ethical approval was given for Experiment 2 by the University of Southampton's Ethics Committee on the 13th of March 2025 (ERGO NUMBER: 95398.A2).

4.7.2 Participants

As with Experiment 1, a priori power analyses were conducted using the *SIMR* package in R (P. Green & MacLeod, 2016; R Core Team, 2023) on pilot data from 15 participants. Target effect sizes were based on prior online interactive search research (Dewis et al., 2025; Godwin et al., 2024) and the findings from Experiment 1. These analyses recommended a minimum sample size of ~40 participants to achieve a power level of 0.80 for an effect size of 0.25. As such, a total of 40 participants were recruited from the online participant recruitment platform Prolific (Age: *M* = 40.88, *SD* = 16.53, Sex: Female = 39.53 %, Male = 60.47 %) during May 2025. Participants were paid £9.00 for taking part.

The Prolific platform allows researchers to set several filters to restrict participation to certain sets of individuals. In Experiment 2, we utilised these tools to apply the following filters when advertising our study: Only include individuals who report themselves as fluent English speakers from the United Kingdom; Only include individuals with a Prolific approval rating of 95% or above. This means that in 95% of the studies they participated in, researchers deemed their data sets as acceptable, with no flaws or failures of attention tests; Only include individuals who have reported having normal or corrected-to-normal vision; Only include individuals who report having normal colour vision. Our reason for switching to a Prolific sample for Experiment 2 and applying these filters was to broaden the demographic range from university students whilst also ensuring the highest possible level of data quality.

4.7.3 Stimuli and Apparatus

The stimuli used in Experiment 2 were identical to Experiment 1. However, an additional manipulation of time was included. As such, depending on which condition a participant was assigned to, some coins took longer to flip than others. In the "Low Entropy Flipped Sooner" condition, the low entropy coins flipped over after only two seconds of chasing, and the high entropy coins flipped over after four seconds of chasing. In the "High Entropy Flipped Sooner" group, the high entropy coins flipped after only two seconds of chasing, and the low entropy coins flipped after four seconds of chasing. This time and effort manipulation has been visually depicted within the bottom panel of Figure 4.2.

4.7.4 Design and Procedure

The procedure for Experiment 2 was identical to Experiment 1 with the only difference being the additional time manipulation. A typical trial is depicted in Figure 4.1.

4.8 Results

4.8.1 Data Cleaning

All data underwent the same preplanned cleaning procedures as Experiment 1 before any analyses were carried out (see Table 4.1). However, we changed the upper time limit cut-off from 60 seconds to 120 seconds to allow for the increase in time it took to flip all four coins. Following all cleaning procedures, the final dataset for Experiment 2 consisted of 4,737 (98.69 %) trials from 40 participants (20 within each time condition).

4.8.2 Analytic Approach

For Experiment 2, the same analytic approach was taken as Experiment 1. However, the models were adjusted to include an additional factor of Time Group (Flipped Later, Flipped Sooner).

4.8.3 Response Accuracy and Response Times

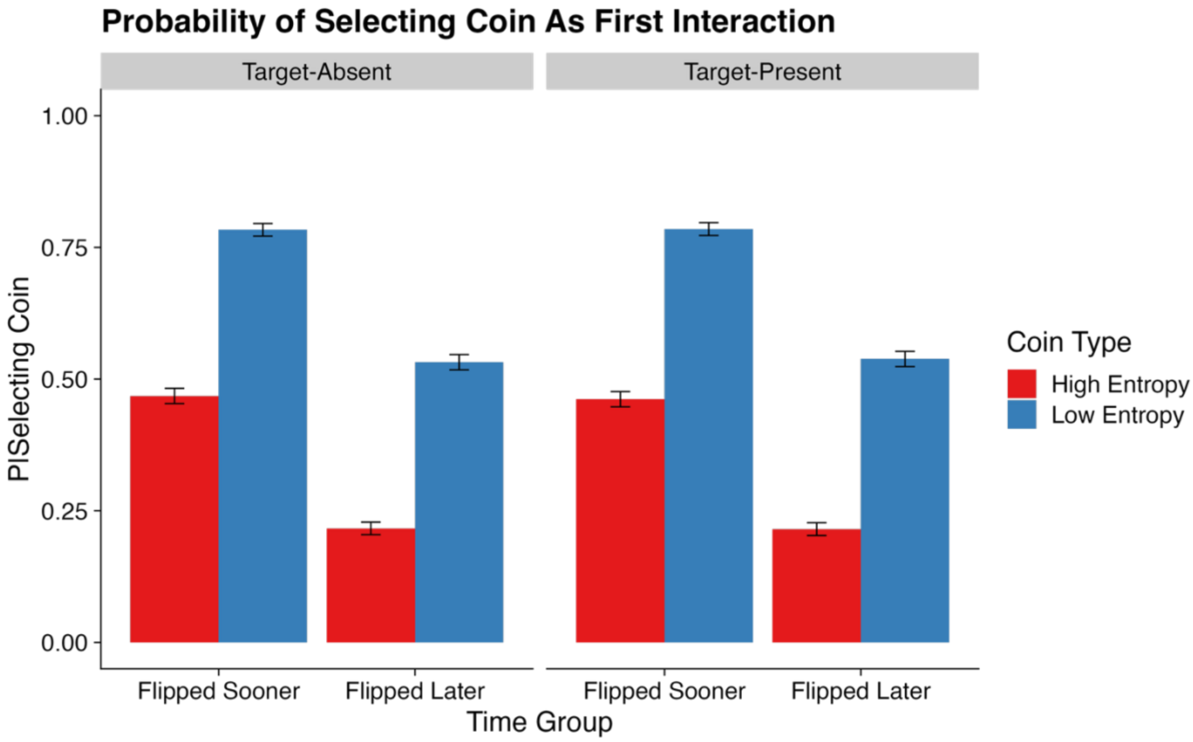
Overall, response accuracy was high for both target-present (M = 0.87, SD = 0.34) and target-absent trials (M = 0.97, SD = 0.16). Likewise, participants completed trials within a reasonable time for target-present trials (M = 12,711.56 ms, SD = 9,392.65 ms) and target-absent trials (M = 19,758.80 ms, SD = 11,959.76 ms). No further analyses were conducted on response accuracy or response times. Our remaining analyses focused on the order of interactions and the number of search objects revealed.

4.8.4 First Coin Selected

As before, we began by examining participants' first interaction choice. Descriptive statistics can be found in Figure 4.7 and model effects and BFs in Table 4.3.

Figure 4.7

Descriptive Statistics for Analysis 4, Experiment 2 – Probability of Selecting Coin First



Note. Errors bars = ± standard error.

Table 4.3

Model effects and Bayes factors for All Analyses – Experiment 2

	Parameter	*Estimate*	*CIs*	*R-Hat*	*BF_{10}*	*OR/IRR*
(A): Analysis 1	Intercept	0.00 (0.02)	-0.05 – 0.05	1.00	0.01	1.00
	Time Group (Flipped Later, Flipped Sooner)	1.15 (0.05)	**1.06 – 1.24**	1.00	**4.13×10^{29}**	3.15
	Coin Type (High Entropy, Low Entropy)	-1.43 (0.05)	**-1.52 – -1.34**	1.00	**9.52×10^{39}**	0.24
	Coin Type × Time Group	0.00 (0.09)	-0.18 – 0.18	1.00	0.09	1.00
(B): Analysis 2	Intercept	-0.00 (0.03)	-0.06 – 0.06	1.00	0.01	1.00
	Time Group (Flipped Later, Flipped Sooner)	0.92 (0.06)	**0.82 – 1.03**	1.00	**1.92×10^{17}**	2.52
	Coin Type (High Entropy, Low Entropy)	-1.47 (0.06)	**-1.58 – -1.36**	1.00	**1.40×10^{32}**	0.23
	Nearest Coin Type (High Entropy, Low Entropy)	0.00 (0.06)	-0.11 – 0.11	1.00	0.06	1.00
	Time Group × Coin Type	-0.00 (0.11)	-0.22 – 0.22	1.00	0.11	1.00
	Time Group × Nearest Coin Type	1.11 (0.11)	**0.89 – 1.33**	1.00	**2.23×10^{11}**	3.03
	Coin Type × Nearest Coin Type	0.13 (0.11)	-0.09 – 0.34	1.00	0.22	1.14
	Time Group × Coin Type × Nearest Coin Type	-0.00 (0.22)	-0.42 – 0.42	1.00	0.22	1.00
(C): Analysis 3	Intercept	0.10 (0.11)	-0.12 – 0.31	1.00	0.06	1.10

Parameter	*Estimate*	*CIs*	*R-Hat*	*BF₁₀*	*OR/IRR*
Presence (Target-Absent, Target-Present)	-0.58 (0.02)	**-0.62 – -0.55**	1.00	**$1.01{\times}10^{37}$**	0.56
Coin Type (High Entropy, Low Entropy)	-0.19 (0.02)	**-0.23 – -0.15**	1.00	**$7.09{\times}10^{8}$**	0.83
Time Group (Flipped Later, Flipped Sooner)	0.14 (0.02)	**0.10 – 0.18**	1.00	**$5.82{\times}10^{5}$**	1.15
Presence × Coin Type	-0.30 (0.04)	**-0.38 – -0.23**	1.00	**$6.19{\times}10^{6}$**	0.74
Presence × Time Group	0.19 (0.04)	**0.12 – 0.27**	1.00	**706.64**	1.21
Coin Type × Time Group	-0.18 (0.39)	-0.94 – 0.59	1.00	0.44	0.84
Presence × Coin Type × Time Group	0.13 (0.07)	-0.02 – 0.27	1.00	0.32	1.13

Note. CIs = Credible Intervals; BF = Bayes Factor; OR = Odds Ratios; IRR = Incidence Rate Ratios; bolded CI values = CIs that did not pass through zero; bolded BF values = BF >3.20. Values in parentheses represent the associated standard error values. Effects were deemed reliable if CIs did not pass through zero and BFs > 3.20.

(A): Analysis 1 = Probability of Selecting Coin as First Interaction.

(B): Analysis 2 = Probability of Selecting Coin as Second Interaction.

(C): Analysis 3 = Total Coins Flipped.

ORs and IRRs have been added to aid interpretation of effects. ORs represent the odds of an outcome occurring. Values > 1.00 indicate that the outcome is more likely to occur and values < 1.00 indicate the opposite. IRRs are used for count data and indicate how frequently an event happens in one group compared to another. Values > 1.00 indicate greater frequency and values < 1.00 indicate the opposite.

Within this analysis, we observed a Coin Type × Time Group interaction. To better understand this interaction, we conducted several post-hoc contrasts. These contrasts highlighted that, overall, participants selected the low entropy coin as their first interaction more often than they did the high entropy coin. However, the magnitude of this difference was modulated by Time Group. Here, the likelihood of selecting a low entropy coin first was much larger when the low entropy coin also flipped sooner (*Estimate* = 2.57, *lower CI* = 2.43, *upper CI* = 2.70, BF_{10} = 3.80×10^{47}) compared to when it did not (*Estimate* = 0.29, *lower CI* = 0.13, *upper CI* = 0.40, BF_{10} = 1.66×10^{3}).

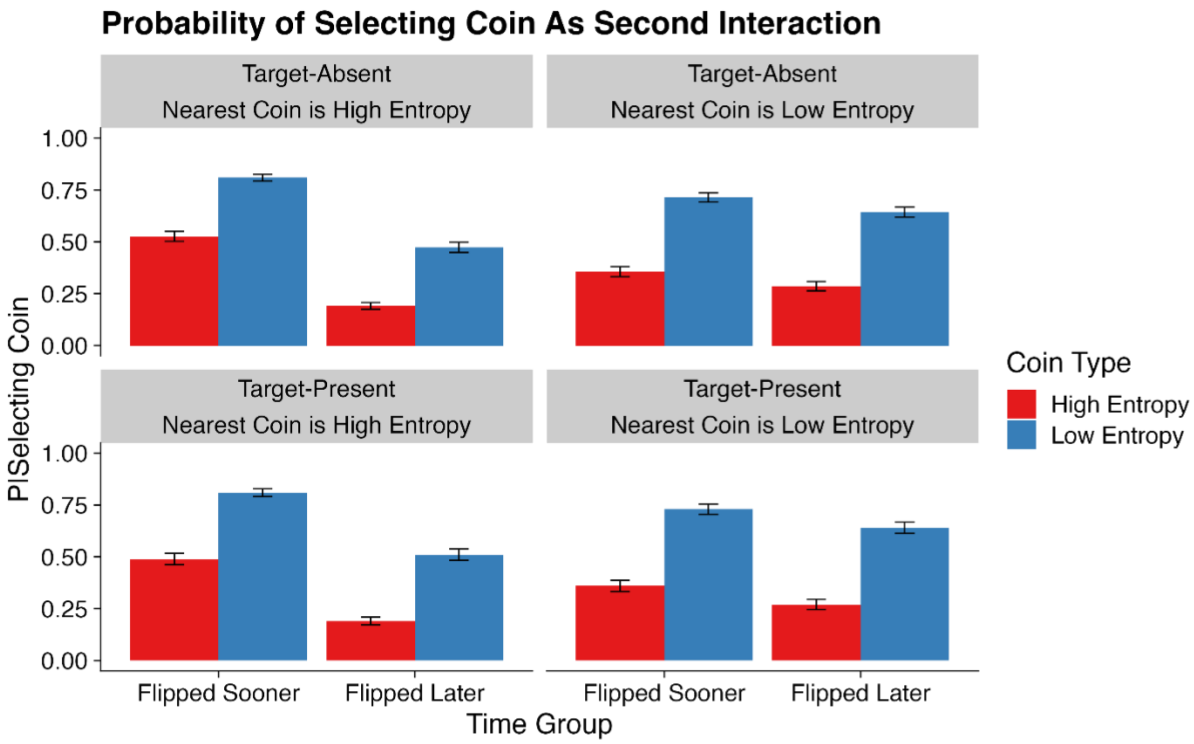
Put simply, when the low entropy coin flipped sooner, participants were a staggering ~57% (0.57) more likely to select it as their first interaction compared to the high entropy coin. In contrast, when the high entropy coin flipped sooner, this difference dropped to ~7% (0.07). Here, in the "High Entropy Flipped Sooner" condition, despite the low entropy coins requiring chasing for a longer duration, it did not appear to offset the aversiveness of the effort required to chase high entropy coins. This was not directly in line with our predictions regarding the influence of time, but does provide support for the effort hypothesis from Dewis et al. (2025).

4.8.5 Second Coin Selected

Next, we examined the likelihood that participants would select a specific coin as their second interaction. As with Experiment 1, we included a factor within the model to keep track of whether the nearest coin was high or low in entropy. Descriptive statistics can be found in Figure 4.8, and model effects and BFs within Table 4.3.

Figure 4.8

Descriptive Statistics for Analysis 5, Experiment 2 – Probability of Selecting Coin Second



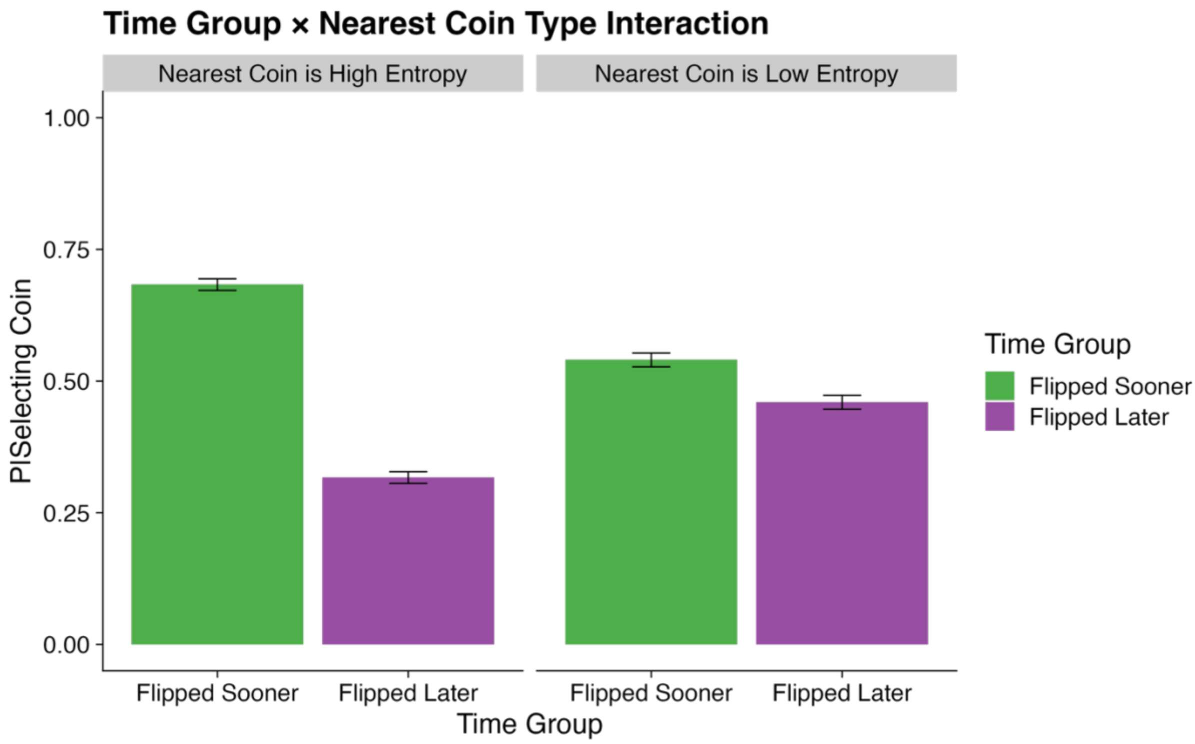
Note. Errors bars = ± standard error.

Within this analysis, we first observed a main effect of Time Group. This suggested that when accounting for other factors, participants tended to select whichever of the two coin types flipped sooner. Next, we found an extremely strong main effect of Coin Type. Here, regardless of other factors, participants were consistently more likely to select a low entropy coin second than they were a high entropy coin.

Lastly, an interaction between Time Group and Nearest Coin Type was observed and further explored using post-hoc contrasts (see Figure 4.9 for a visualisation of this interaction). These post-hoc examinations revealed that participants selected the coin that flipped sooner more often than the one that flipped later regardless of whether the nearest coin was high in entropy (*Estimate* = -1.48, *lower CI* = -1.63, *upper CI* = -1.33, BF_{10} = 1.07×10^{26}) or low in entropy (*Estimate* = -0.37, *lower CI* = -0.53, *upper CI* = -0.21, BF_{10} = 487.27). However, this effect was substantially stronger when the nearest coin was high entropy. Thus, suggesting that participants were on occasion willing to look past increases in time but only when the nearest coin to them was low in entropy.

Figure 4.9

Visualisation of Time Group × Nearest Coin Type Interaction



Note. Errors bars = ± standard error.

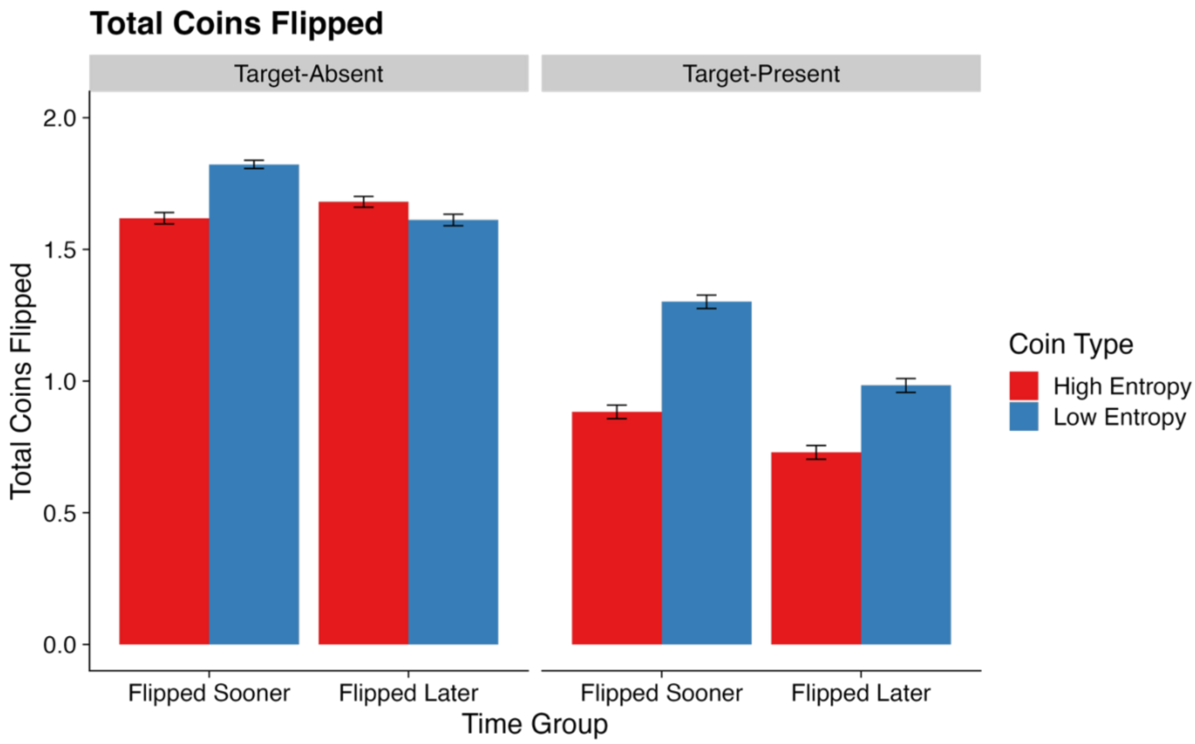
To summarise, both time and effort played a role within participants' selections. Participants' second selection choices were predominately to either low entropy coins, or whichever of the two coins flipped sooner. Additionally, at times participants were willing to ignore increases in search duration provided that the nearest coin to them was low in entropy. These findings were not directly in line with our predictions regarding time but do further highlight an important intertwined relationship between effort and time.

4.8.6 Total Coins Flipped

Finally, we examined the number of coins flipped within each trial as a function of Presence, Coin Type, and Time Group. Descriptive statistics can be found in Figure 4.10, and model effects and BFs within Table 4.3.

Figure 4.10

Descriptive Statistics for Analysis 6, Experiment 2 – Total Coins Flipped



Note. Errors bars = ± standard error.

This analysis revealed several effects all of which were subsumed by a Presence × Coin Type interaction and a Presence × Time Group interaction. Both interactions were further examined using post-hoc contrasts.

Beginning with the Presence × Coin Type interaction, our contrasts revealed that participants flipped a greater number of low entropy coins compared to high entropy coins within target-present trials (*Estimate* = 0.34, *lower CI* = 0.28, *upper CI* = 0.40, BF_{10} = 9.09×10^{12}) but not within target-absent trials (*Estimate* = 0.04, *lower CI* = 0.00, *upper CI* = 0.08, BF_{10} = 0.09). Next, within the Presence × Time Group interaction, analyses revealed that participants flipped more of the coins that flipped sooner than the ones that took longer to flip within target-present trials (*Estimate* = -0.24, *lower CI* = -0.29, *upper CI* = -0.18, BF_{10} = 4.05×10^{5}) but not within target-absent trials (*Estimate* = -0.04, *lower CI* = -0.09, *upper CI* = 0.00, BF_{10} = 0.12).

Both interactions highlighted a bias towards what participants perceived to be the easier of the two coins. If participants predominately selected a particular coin type, then in trials where all four coins did not need to be flipped (i.e., target-present trials), an overall increase in the number of flips for these coins should occur when summated across all trials. As with all other analyses, this was not directly in line with our predictions regarding the influence of time but does further highlight the combination of time and effort within interactive search. However, between these two, the strongest effect was the effect of entropy (effort).

4.9 Discussion

The findings from Experiment 1, where time was held constant, neatly highlighted that despite an influence of effort, time still likely plays a role in making effortful tasks aversive. However, it remained unclear which of the two between effort and time was the driving force within attentional selection. As such, we addressed this within Experiment 2. As before, we did so by asking participants to engage in an interactive search task for a target T shape attached to the underside of a virtual coin. However, participants were additionally split into one of two time conditions where either the low or high entropy coin required chasing for a longer duration.

Based on both Experiment 1's findings and the previously mentioned reviewer comments, we took the stance that time would be the main driver of attentional selection within these effortful tasks. Therefore, we predicted that participants would prioritise selections with whichever of the two coin types required chasing for the least time, regardless of any associated effort.

Overall, our results showed a consistent interaction between time and effort within our task. However, this interaction was not directly in line with what we predicted. Here, we observed a bias towards low entropy coins within first and second selections across each trial and the total number of coins flipped. Across all measures, this effect was strongest when low entropy coins also required less time chasing. In contrast, when high entropy coins required less time chasing, participants became considerably more varied in their selections but still predominantly chose the low entropy coins. In other words, time does appear to influence attentional selection, but only when paired with increased effort. This is likely why Dewis et al. (2025) observed such strong effects within their experiments, since their high effort manipulation also inadvertently resulted in increased interaction durations. Indeed, effort and time appear to be closely intertwined. However, within our interactive search experiments, effort appears to be the predominant driving force of attentional selection between the two.

4.10 General Discussion

The starting point for this current project was a series of prior experiments we conducted that examined attentional selection within interactive search, specifically focusing on the role of effort (Dewis et al., 2025). Within these experiments, participants searched for a T shape embedded onto the side of a set of virtual cubes. Across both experiments, the effort required to interact with cubes was varied. Overall, we concluded that searchers adopted an easy-first strategy, focusing on objects that could be easily, or with little effort, rejected as distractors or accepted as containing a target. However, we had overlooked a potential confound within our paradigm: not only did high effort stimuli require more effort, but they also inadvertently required more time to examine as well. As such, we deemed it important to verify whether our previous results were due to the search system prioritising objects that could be searched more rapidly, rather than with less effort.

We addressed the confound of time directly across two new sets of experiments wherein we carefully manipulated and controlled for time within effortful interactive search. Participants searched for a target T shape attached to the underside of a set of four virtual coins. Across both experiments, participants selected coins using their computer cursor. Following a selection, the coin moved around the display, and the participant chased it with their cursor, repeatedly interacting with it until it would “give up” and flip over to reveal the obscured T or L shape attached to its underside. Within each trial, coins were either easy or hard to interact with based upon a set of predetermined factors (entropy and time). Colours were applied to the coins to ensure participants could differentiate and form associations with specific coin types, i.e., a red coin may have been perceived by the participant as the hardest coin to interact with and so forth. Our predictions were drawn from prior research into attentional selection (Awh et al., 2012; Wolfe, 2021; Wolfe & Horowitz, 2017) and our own prior research on effortful interactive search (Dewis et al., 2025).

In Experiment 1, we began by investigating the role of effort whilst carefully controlling for time spent interacting. Two of the four coins within each trial were high in entropy and moved in a quick and unpredictable manner, making them effortful to track and interact with. In contrast, the remaining two coins moved in a slow and predictable manner, making them less effortful to track and interact with (low entropy). To control for time spent interacting, each coin only moved around the display for a total of two seconds before flipping over. We predicted that participants would become biased towards selecting low entropy coins over high entropy coins in an attempt to reduce the effort involved in search. Overall, this was indeed what we observed within our results. However, the observed effects were more varied and slightly weaker than those found within our prior research (Dewis et al., 2025).

In Experiment 2, we further investigated the role of time within effortful interactive search. We utilised the same approach as Experiment 1 with an additional time manipulation integrated into the paradigm wherein some coins required chasing for longer (4 seconds) than others (2 seconds). Based upon Experiment 1’s findings, we predicted that participants would display a bias towards selecting objects that would flip sooner. However, our findings did not consistently show this. Instead, our results had two clear takeaways. First, participants prioritised selections with low effort coins over the coins that flipped quickly. Second, when high effort objects took longer to flip, participants developed an extremely strong bias towards selecting the low effort objects instead. This suggests that the influence of time was dependent upon the associated effort that was required during that period of time.

Next, we return to the overarching aim of the paper, determining whether Dewis et al. (2025) were correct in their conclusions that searchers will prioritise interactions with objects that require the least effort to interact with. From a strategic standpoint, under the *Performance Maximization account* (e.g., Rachlin et al., 1981), searchers should choose a strategy that produces the greatest overall benefit to cost ratio whilst still allowing for the completion of the task as accurately and quickly as possible. Within our task, an optimal strategy would therefore have been to prioritise coins that flipped sooner. However, participants did not take this approach. Whilst surprising, these findings align closely with numerous accounts of suboptimal search strategies within visual search (Bacon & Egeth, 1994; Folk & Anderson, 2010; Irons et al., 2012). Likewise, although not nearly as effortful as our interactive search task, when taking effort into account within visual search, as was the case here, there are several examples of individuals avoiding effortful tasks despite it being the quicker and more optimal approach (Irons & Leber, 2016, 2018; T. Zhang & Leber, 2024). We conclude that across both interactive and visual search tasks, the decision regarding which objects to examine is determined both by the effort and time required to examine them. However, within our interactive task, our results suggest that between the two, effort appeared to be the predominant factor driving attentional selection.

These findings once again bear particular importance for real-world practical applications of interactive search. Our results suggest that within real-world scenarios, searchers will de-prioritise interactions with objects that indicate either a high level of effort or time to engage with. Furthermore, objects that are both high effort and take a large amount of time to engage with or examine – for example, searching through and moving many heavy objects within a toolbox – will be deprioritised substantially more than those which will take less time and effort. What is currently unclear, however, is the extent to which these findings will generalise to interactions with real-world physical objects, and whether the basic principles here can be replicated beyond a computer screen and virtual interactive search.

Overall, then, whilst we still agree that searchers take an easy-first approach when conducting interactive search tasks, we believe it is important to consider time within this conclusion. Tasks that are both high in effort and high in time will be perceived as more aversive than high effort tasks that can be completed quickly. As such, we conclude that searchers first use a combination of both effort and time to determine what makes an object “easy” or “hard” to interact with in relation to all other objects, before prioritising interactions with said easier objects.

Chapter 5 General Discussion

Historically, researchers have explored human search behaviours by conducting experimentation using static two-dimensional displays. In these experiments, searchers are typically tasked with finding a target object amongst stationary distractor objects or scenes (see Wolfe, 2020b for a review). The swathes of research findings and theoretical models produced using this approach have one crucial limitation; they overlook the role of interactions within search. Outside of the laboratory, it is very rare indeed that a search will proceed without some form of interaction with the environment from the searcher (e.g., Hout et al., 2022; Riggs et al., 2017, 2018; Sauter et al., 2020). The central purpose of this thesis and the empirical studies conducted throughout was to address this missing link by conducting search experiments that were interactive in nature. Specifically, these experiments focused upon the factors that drive cognitive decisions regarding which objects or areas to interact with, and how exhaustively to search these before termination.

This final chapter will begin by detailing the key findings from the studies presented throughout this thesis, followed by how these findings contribute and align with the broader literature presented within Chapter 1. Finally, any limitations will be detailed and the potential directions for future research discussed.

5.1 Summary of Experiments and Findings

Study 1: Do searchers terminate their searches before revealing all obscured visual information during an interactive search?

In Chapter 2, the results of two varied target prevalence interactive search experiments were presented. These experiments focused on how the prevalence effect (see Horowitz, 2017 for a review) manifests itself within interactive search, with a specific focus on whether shifts in prevalence influence how exhaustive searchers are and how these compare to visual search findings. Across the two experiments, participants completed a virtual interactive search task that involved manipulating and rotating sets of virtual cubes. Participants searched for a target T shape printed onto the side of one of the cubes. The target T shape appeared on either 50 % (high prevalence condition) or 10 % (low prevalence condition) of trials. In Experiment 2, the number of cubes to search through per trial was increased with the goal of better understanding the quantity of visual information participants were willing to leave unchecked when the requirements for an exhaustive search increased.

Across both experiments, results were remarkably consistent. Participants were unwilling to terminate target-absent trials before having revealed all the faces of all cubes. This finding was unaffected by both target prevalence and set size; however, the standard effects of low target prevalence were still observed upon response accuracy but not within RTs. As discussed in Chapter 2.4, since prevalence had no observed effects upon search exhaustive measures, the detected decline in response accuracy for those in the low prevalence condition was not entirely for the same reasons as those found within low prevalence visual search (e.g., Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015; Wolfe et al., 2005, 2007). Instead, it appears that searchers operated under a ‘no stone unturned’ approach. Here, searchers were unwilling to provide an ‘absent’ response without checking most – if not all – possible places, regions or areas in a display that could contain a target.

Study 2: What factors influence object selection within interactive search?

In Chapter 3, the results of two independent experiments that investigated the influence of effort and patch value (the perceived value assigned to different areas containing resources, e.g., Charnov, 1976) on object selections within interactive search were presented. For these experiments, a modified version of the methodology used in the experiments shown within Chapter 2 was utilised. Participants were again asked to interactively search through a set of virtual cubes for an attached target T shape. However, in Experiment 1, the physical effort required to manipulate cubes was varied. Here, half of the cubes within each trial were made to be physically effortful to rotate by reducing their sensitivity to mouse inputs in comparison to the remaining cubes. In Experiment 2, patch value was manipulated by varying the quantity of shapes attached to the side of cubes. Within each trial, half of the cubes were made to be “information-rich” (e.g., Nahari & El Hady, 2025) by embedding a shape onto each face of the cube, and the remaining half were made to be “information-poor” by embedding only a single shape onto the cube. Across both experiments, colour of cubes was used to differentiate cube types: this allowed participants to identify cube types without needing to physically interact with them first.

Overall, these findings suggested that the perceived effort required to interact with an object was an extremely strong driver of attentional selection within interactive search. In Experiment 1, participants consistently prioritised interactions with low effort cubes over high effort cubes. However, in Experiment 2 contrary to prior work regarding patch value and optimal search strategies (e.g.,Charnov, 1976; Ehinger & Wolfe, 2016; Nahari & El Hady, 2025; Wolfe, 2013; J. Zhang et al., 2017), participants prioritised interactions with information-poor cubes. Nevertheless, as discussed within Chapter 3.10, the reason for this effect was not a result of patch value, but instead a result of effort reduction. Here, information-poor cubes could be rapidly processed with little effort due to their lack of visual information. These two experiments combined highlighted that during interactive search, searchers would adopt an “easy first” strategy, focusing on objects that can be rapidly, easily, or with little effort, rejected as distractors or accepted as containing a target.

Study 3: What role does time play in making search effortful and how does this influence interactive search strategies?

Within the previous experiments presented in Chapter 3, the potential confound of time was overlooked. Increases in effort typically coincide with increases in time, e.g., a heavy object will often take longer to pick up and carefully inspect than a lighter one would. As such, the extent to which time was influencing object selection within the previous experimental design could not be disentangled. This shortcoming was addressed across the two independent experiments that were presented within Chapter 4. Across both experiments, participants were asked to conduct an effortful interactive search for a target T shape attached to the underside of a set of virtual coins. To reveal the obscured visual information, participants had to “flip” coins by clicking on them with their computer cursor. However, to ensure effortful interaction, following the initial selection, the coin moved around the display, requiring participants to chase it with their cursor before it flipped over. In Experiment 1, effort was varied via the entropy of coin movement whilst ensuring the time taken to interact remained constant between all coins. In Experiment 2, the role of time was further explored by varying both the effort and time required to interact with certain coins.

In Experiment 1 when time was held constant, participants continued to prioritise objects that required the least effort to interact with, supporting the findings presented from Chapter 3. In Experiment 2 however, the results had two clear takeaways. First, participants prioritised selections with low effort coins over the coins that required the least amount of time to flip. Second, when high effort coins took longer to flip, participants developed an extremely strong bias towards selecting the low effort coins instead. The influence of time upon attentional selection was therefore dependent upon the associated effort that was required during that period of time. Searchers therefore first use a combination of both effort and time to determine what makes an object “easy” or “hard” to interact with in relation to all other objects, before prioritising interactions with said easier objects.

5.2 Contributions to the Current Literature

The overall aim of this thesis was to better understand how searchers determine which objects or areas to interact with during interactive search tasks, and how exhaustively to search these before stopping. As shown throughout Chapter 1, the development of key theoretical models and understandings of human search behaviour (e.g., Treisman & Gelade, 1980; Wolfe, 2021; Wolfe et al., 1989) relied heavily upon experimentation using static two-dimensional displays. However, when considering search tasks outside of the laboratory, it is rare that these tasks are static in nature. Despite this, literature into interactive search is limited. Whilst some key studies have explored differences between interactive and visual search (Gilchrist et al., 2001; Hout et al., 2022; Sauter et al., 2020; A. D. Smith et al., 2008), to date, none have investigated the factors that guide interaction choices in detail.

The following subsections will therefore discuss the contributions and implications of this thesis and its associated findings in the context of the broader visual search literature and limited interactive search literature.

5.2.1 Replicable Methodology

Over the years there have been several attempts to create a replicable and adaptable methodology for conducting interactive search tasks, including utilising LEGO® as stimuli (Hout et al., 2022; Sauter et al., 2020), GPS tracking (Riggs et al., 2017), frame-by-frame video analysis (Riggs et al., 2018), and virtual drag and drop designs (Solman et al., 2012). Whilst innovative, these designs are either excessively complex, unadaptable, or unable to collect the rich quantity of data required to better understand interactive search. This is problematic for a number of reasons, but most importantly it makes conducting interactive search tasks inaccessible for most researchers. Indeed, the limited knowledge and equipment required to create visual search tasks with static displays is likely why it became such a prolific method for assessing visual search.

A methodology that addresses these issues directly has been developed throughout this thesis. This methodology utilises pre-built open-source software (Danchilla, 2012; De Leeuw, 2015) that is accessible to all researchers. As demonstrated across the six experiments throughout this thesis, this methodology is capable of automatically capturing large quantities of rich data thus enabling a wealth of analysis options beyond simple RT and accuracy measures. Indeed, across all experiments, this methodology has enabled the application of numerous measures – inspired by those used within eye tracking (see Godwin et al., 2021 for visual search examples) – that were otherwise previously not possible. Likewise, this thesis has demonstrated the methodology's ability to be adapted from simple designs such as those in Chapter 2 to far more advanced interactive scenarios such as those detailed within Chapter 4. This accessibility and adaptability is paramount in ensuring the advancement of understandings of interactive search. Finally, whilst not explicitly explored within this thesis, this methodology has the capacity for strict control over lighting, colour profiles, and many other metrics that can influence the validity and reliability of results (e.g., Hurlbert & Yu, 2025; Witzel & Gegenfurtner, 2018).

5.2.2 No Stone Left Unturned

The fundamental difference between interactive and visual search is the requirement that the searcher engage in a physical interaction or manipulation of the environment (Hout et al., 2022; Sauter et al., 2020). This difference has direct implications upon a searcher's ability to exhaustively search environments. During a standard visual search task, by the time the searcher terminates the search, all possible visual information has been made available to the searcher. In contrast, during an interactive search, the quantity of visual information presented to the searcher is dependent upon how exhaustively the searcher interacts with the environment, i.e., how much obscured visual information they decide to uncover. Within visual search, the exhaustiveness of search has typically been examined through RTs and eye movement measures (Godwin et al., 2021).

There is substantial literature investigating the many factors that drive exhaustiveness and search termination times within visual search (for a review see Wolfe, 2012). Typically, declines in search exhaustiveness manifest themselves as reductions in fixations of objects (Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015), reductions in the time spent carefully inspecting the objects they do fixate (Peltier & Becker, 2016) and increases in rapid search terminations (Wolfe et al., 2005, 2007). Whilst declines in search exhaustiveness have been well established within visual search, the six experiments presented within this thesis have consistently shown this not to be the case for interactive search. It appears that regardless of how likely it is that the searcher believes the target to be present, the effort required to check, or the time it takes to do so, searchers are unwilling to terminate their searches before having revealed all possible visual information. In other words, they leave no stone unturned.

The most likely explanation here is that compared to visual search, where searchers may account for their reduction in exhaustiveness by relying on their less accurate peripheral vision (e.g., Lleras et al., 2022), in interactive search, it is impossible to confidently reject areas that cannot be seen by the searcher. It is important to also consider the methodological design of the experiments presented throughout this thesis and their potential influence upon search exhaustiveness. By its very nature, the design forces seriality to individual's search approaches. If participants want to search in an entirely effectively manner, then they must engage in a serially exhaustive search to reveal all obscured visual information. Whilst this is similar to what occurs within real-world interactive search tasks, e.g., a searcher will go from object to object as they search for items, it restricts the ability to compare findings to some of the parallel models mentioned within Chapter 1 (e.g., Palmer, 1995; Palmer et al., 2000; Verghese, 2001). This is not to say that these models are incorrect but that instead the seriality of the task may override potential benefits of parallel processing. In other words, in visual search tasks where parallel processing of all visual information within the scene is plausible, search exhaustiveness, as measured by object fixations, may not be necessary if it can be handled by initial parallel processing alone. This is simply not the case for the methodologies used throughout this thesis. Perhaps, forcing searchers to wait before engaging in their interactive search may allow parallel processing of the currently available visual information to occur before attention is directed to their first interaction object and could provide more insight into this.

Likewise, search exhaustiveness should not be considered without acknowledgement to the capacity of visual short-term memory. Although there has been some debate around whether search has memory, the consensus seems to now be upon the idea that search has a limited memory for already-inspected objects (Kristjánsson, 2000; Le-Hoa Võ & Wolfe, 2015; Peterson et al., 2001; Wolfe et al., 2005). In other words, during a search task the searcher must keep a record of already seen objects in their visual short-term memory. Within visual search, this limit is believed be around four items (Cowan, 2001; Sewell et al., 2014). Across Chapters 3 and 4, the set size for objects to be searched (the Ts and Ls attached to the sides of the four cubes) was 24 objects per trial, similar to that of normal visual search tasks (Wolfe, 2020). In our task, participants seeking to search exhaustively would need to remember which cubes they had already searched (a value between zero and four), and then, for each cube, they would need to remember and maintain a representation of which faces of the currently examined cube had already been inspected. Perhaps then, it is the case that search exhaustiveness within these tasks is born not out of explicit choice but out of necessity. It may be the case that searchers simply do not have the capacity within visual short-term memory to keep track of which faces of a rotating cube have been checked already and which are new and appearing for the first time. A consequence of this is that it can become hard for a searcher to trust and judge their own ability to detect a target once made visible. Instead, searchers may believe that they have revealed, missed, and re-hidden a target, thus resulting in an extremely high level of search exhaustiveness and rechecking of objects compared to visual search tasks.

Nevertheless, the limit of peoples' willingness to search exhaustively remains unknown. Although the tasks conducted throughout this thesis were both effortful and challenging, it appears that the costs of doing so did not outweigh the cost of leaving visual information unchecked. Of course, there are tasks where it is physically impossible to exhaustively check all area, such as Riggs et al. (2017), where participants searched through a large grass field, or

Riggs et al. (2018), where participants searched through a fully furnished house. As such, this suggests that the threshold required for searching less exhaustively must still exist, it is simply much higher in interactive search than visual search. Whilst the only current model of interactive search, the i-MDM (Hout et al., 2022), does consider search termination within their model, there is no mention of the extent to which an individual will search areas or objects before terminating their searches. The findings from this thesis therefore further support the notion that, should we wish to accurately model interactive search, then models must not only acknowledge but better account for the role of search exhaustiveness.

5.2.3 The Important Role of Effort

The role of effort, both cognitive and physical, upon search behaviours is a factor that should not be overlooked within the interactive search literature. Although eye movements require a small amount of physical effort (Araujo et al., 2001) and visual search can be made cognitively effortful by increasing perceptual load (Lavie, 1995; Lavie et al., 2014; Lavie & Tsal, 1994; Matias et al., 2022), these effects are small in comparison to interactive search. From a cognitive standpoint, interactive searches require a combination of two simultaneous processes. One to control physical body movements for interactions with the environment and a second to control visual attention for identification of targets (Goodale & Milner, 1992; Jeannerod, 1994). Indeed, it has been shown that having to juggle these two processes at once can negatively impact task performance when searching (Park et al., 2021; Solman et al., 2012). As such, when considering only cognition, interactive search produces more load and effort than comparable visual search tasks. Furthermore, when considering the role of physical effort in search, the additional requirement of upper-limb movements in interactive search is substantially more effortful than eye movements (e.g., Morel et al., 2017; Steelman et al., 2011; Wang et al., 2021; Wickens, 2014, 2015). Despite this, within the limited research conducted on interactive search, the role of effort has been vastly overlooked.

The studies presented across Chapters 3 and 4, have shown that effort, both physical and cognitive, is an extremely powerful driver of object selection within interactive search. Across all experiments, participants consistently engaged in strategies that minimised interactions with high effort objects. It is not necessarily surprising that searchers chose to avoid effortful interactions. Indeed, even within visual search tasks where very little effort is required, searchers have been shown to avoid effortful tasks (Irons & Leber, 2016, 2018; T. Zhang & Leber, 2024) even when doing so was less optimal (Bacon & Egeth, 1994; Folk & Anderson, 2010; Irons et al., 2012). The surprising factor here is the extent to which the physical cost of interactions has been overlooked throughout the search literature. This is particularly poignant given that the ability to physically interact with objects directly influences one's ability to accurately detect the target. Although trivial for a simulated search task within the laboratory, the findings across these experiments bear particular importance for real-world practical applications of interactive search. Here, findings suggest that searchers will de-prioritise interactions with objects that indicate either a high level of effort or time to engage with. Whilst search exhaustiveness was high across these effortful laboratory experiments, in real-world search tasks – such as search and rescue teams searching through open terrain or buildings (e.g., Riggs et al., 2017, 2018) – physical effort and fatigue become a substantially more prominent confound. As such, perhaps it would be the case that searchers would become more inclined to leave high effort objects or areas unchecked altogether.

The data produced from the studies throughout this thesis provide important insight into determinants of selection choice during interactive search. Despite the clear connection between effort and interaction, as was the case for search exhaustiveness, the only current model of interactive search (Hout et al., 2022) makes no mention of the effort required to search, nor the impact this may have upon object selection or search termination. These findings therefore provide more evidence for the need to update current models of interactive search to account for such a paramount factor.

This prompts an important and logical next question: how should one update current models of search to account for these findings? To answer this question, we must return to the prominent Guided Search 6.0 model of search that stipulates attentional selection is guided by a priority map. This priority map uses a weighted summation of top-down and bottom-up inputs in addition to many other factors that work in tandem to influence attentional selection in a "winner takes all" approach regarding map activation (Godwin et al., 2014; Wolfe, 2021; Wolfe & Horowitz, 2017). Since interactive search is an extension of visual search there is nothing inherently incorrect about this model of search, however, one could envision an adaption to the model by which it may extend and branch into a new section to account for search tasks where interactions are involved. Within this section the role of effort should be explicitly included as an inhibiting influence upon the priority map. Of course, effort could be encompassed within the top-down input section of GS6 and considered as a "goal" of the searcher with the aim of reducing effort. However, as explained throughout this thesis, the role of effort appears to be more prominent within interactive search than visual search, as such, models should emphasise this when branching into this new interaction section.

Perhaps, then, the better approach is to do as Hout et al. (2022) have done and build a separate yet highly related search model specific to interactive search with its roots in GS. Under this approach, it is straightforward to update their model with a simple additional 2AFC regarding perceived effort required to interact with an object and an update to their search termination sections acknowledging the high-level search exhaustiveness thresholds that seems to be applied to interactive searches.

5.3 Key Takeaways

The key results presented throughout this thesis will now be summarised:

1. ***Search Exhaustiveness***
   Regardless of their perception of target prevalence, effort, or time, participants were extremely exhaustive in their searching. Participants typically did not terminate target-absent trials before revealing all faces of the cubes or coins.

2. ***Effort***
   Effort, both physical and cognitive, is an extremely strong and aversive factor that guides attentional selection within interactive search. Participants prioritised selection with objects that could be easily or quickly processed during interactive searches.

3. ***Time***
   The time it takes to interact and check an object is an important factor that guides attentional selection. Participants prioritised selections with objects that minimised the time taken to complete the task. However, participants were willing to overlook increases in time if the alternative option required high effort. Time and effort are closely related factors that should not be overlooked within interactive search.

5.4 Limitations and Future Steps

5.4.1 Limitations

Every step was taken to reduce limitations across the experiments presented within this thesis. However, there are indeed some aspects that would benefit from being adjusted in future research, as will now be discussed.

Although the methodology utilised was novel and worked extremely well for its intended purpose, when compared to real-world search tasks, it was still simplistic in nature. This is a prevalent issue that has long been a drawback of the visual search literature also (Nicholson & Prinz, 2022; Wolfe, 2020a). However, in contrast to visual search, the interactive methodology developed throughout this thesis can be easily adapted to allow for recreation of realistic interactive scenes and collection of associated interaction data. Despite this, the use of simplistic stimuli limits the generalisability of these findings to some extent. The choice to not experiment with more complex real-world scenes was that very little is currently known about interactive search. There are no consistent measures or methodologies as there are within visual search (Chan & Hayward, 2013; Wolfe, 2020b). As such, the studies throughout this thesis were utilised as a means of developing and proving measures, centred around the search literature presented with Chapter 1, that could then be later applied to and tested within more complex real-world situations.

The second limitation concerns the ability to manipulate physical effort within the digital realm. As has been shown throughout this thesis, the role of effort is a vital factor within interactive search. Whilst manipulating cognitive effort within virtual paradigms is relatively straightforward – e.g., increasing cognitive or perceptual load (Lavie, 1995; Lavie et al., 2014; Lavie & Tsal, 1994) – increasing physical effort is much harder. Within the non-digital realm, increasing the required physical effort is as easy as increasing the weight of an object. Here, heavier objects require more physical effort and energy to manipulate than lighter objects. Although note the important confound of time that this approach introduces. Within the digital realm, the effort of interaction within the experiments from Chapter 3 were increased by reducing the sensitivity of mouse inputs, resulting in more physical clicks and drags of the mouse. Likewise, in Chapter 4, the entropy of coin movements was increased resulting in participants needing to physically move the mouse more to chase the coins. Whilst this increased physical effort enough to be aversive to participants, in contrast to effortful real-world interactive searches (e.g., Riggs et al., 2017, 2018), these tasks are less effortful. However, this does not mean that this is the only way to increase effort within virtual interactive search tasks. The role of physical effort within visual search has been explored using hand grip devices where participants must effortfully exert force on a device whilst searching (Anderson et al., 2025; Park et al., 2021). The current methodology could easily be adapted to include this. Likewise, research into user accessibility has utilised gloves to restrict hand movement (e.g. Goodman-Deane et al., 2016). The same approach could be taken to restrict movement and thus increase effort within the current virtual paradigm. To our knowledge neither of these have been explored within interactive search as of yet.

5.4.2 Future Steps

In this thesis, the necessary initial steps were taken to allow for better understanding of interactive search. A replicable and adaptable methodology was developed and its effectiveness proven, along with several different new measures, across six experiments. As mentioned within Chapter 1, given the limited available interactive search literature, this thesis and associated experiments should be considered as just the beginning for interactive search. Therefore, as will now be discussed, there are a number of key avenues that future experiments and research should explore.

The role of reward: The role of effort within interactive search was thoroughly explored throughout this thesis. However, a factor that coincides with effort is reward and consequently, punishment. The role of reward within decision making has been studied extensively from a neuroanatomical standpoint (see Schultz, 2006 for review). As such, it has been well established that as humans we seek rewards and avoid punishments (Cohen & Blum, 2002). Indeed, there has been substantial work within visual search that has highlighted the important role of reward on guiding attentional selection (Awh et al., 2012; Dayan & Balleine, 2002; Della Libera & Chelazzi, 2006). However, this is yet to be considered within interactive search. Let us consider a common real-world situation. An airport screener must interactively search through a packed bag full of heavy items for any restricted dangerous objects. The effort required to do so is large, however, the consequence of missing a potential target is severe. Likewise, the reward of finding a rare and dangerous target is likely also very large indeed. Perhaps it is the case that if the consequences or perceived reward is high enough, searchers may be willing to ignore the additional effort required to search high effort objects or even prioritise selections with these objects first. Future research would therefore benefit from carefully investigating this connection through the many approaches currently available, e.g., utilising monetary rewards (Della Libera & Chelazzi, 2006).

Eye Movements: Eye movements have proven to provide invaluable insight into search behaviours during visual search tasks that have enabled advancements within the modelling of visual search behaviour (Godwin et al., 2021; Liversedge et al., 2011). Whilst the current approach presented throughout this thesis has excelled in providing a way to assess physical object selection and interactive search behaviour, it does not assess the potential role of eye movements within the visual portion of interactive search. Across the first two studies, although it is likely that participants fixated upon the object of interest at the start of a rotation (e.g., Anwyl-Irvine et al., 2021), it is not clear whether participants consistently tracked the object of interest throughout this interaction or whether they were instead glancing at the cursor position, or momentarily looking at other cubes to plan their future interactions; a rather illogical strategy that occurred within Solman et al.'s (2012) virtual interactive search experiment. Likewise, it may be the case that although individuals remain highly exhaustive in their searching, their true rate of fixation upon objects may be impacted as it is within visual search (e.g., Godwin, Menneer, Riggs, et al., 2015; Hout et al., 2015; Peltier & Becker, 2016). Future research would therefore benefit from utilising the current paradigm paired with eye tracking to better understand the role of visual attention within interactive search.

Into the Physical Realm: Most importantly, future research should aim to expand these studies into the physical real world. Whilst virtual interactive search tasks are a valid form of interactive search, there are many aspects that may vary when taken into the physical realm. Interaction with objects in the real world typically requires more physical body movements and cognitive processing than their virtual counterparts (e.g., Goodale & Milner, 1992; Jeannerod, 1994). For example, in Chapter 3, whilst individuals were willing to expend resources to inspect cubes that contained very little in the way of visual information, this may have been due to the low effort required to move a computer mouse and check. In a real-world replication, this may no longer be the case given that they would need to physically move their body to a greater extent and thus expel a greater quantity of energetic resources. Indeed, the role of arm and body movements is known to heavily influence behaviours within real-world tasks (Morel et al., 2017; Wang et al., 2021). Moreover, in the real world, there are a potential number of other techniques that searchers may use to reveal obscured information without object manipulation (e.g., head movements), that are not possible to achieve within the current virtual paradigm. These factors are argument enough to consider replication of these experiments within real-world settings. Furthermore, increases in accessibility to three-dimensional motion tracking equipment (Naeemabadi et al., 2019; Napoli et al., 2017; Pfister et al., 2014) and advancements in computer vision (Culjak et al., 2012) make the tracking of objects and human interaction more achievable than ever before.

5.5 Concluding Remarks

The present thesis took the initial steps needed to begin addressing the missing link of physical interactions during search. Specifically, this thesis has provided evidence and improved understandings of the factors that drive cognitive decisions regarding which objects or areas to interact with, and how exhaustively individuals will search these before termination. Overall, it is clear that the behaviours conducted during visual search are not a good approximation of those conducted during interactive search. Primarily, interactive search breeds a level of exhaustiveness that is not present within visual search. Furthermore, interaction choices are heavily influenced by the effort and time required to interact with objects. Still, as discussed within this chapter, there are a number of factors that future work needs to explore to gain a more complete account of interactive search behaviours. Primarily, future work will need to focus upon how the factors explored within this thesis interact with perceived reward and eye movements, and how well the current findings generalise to physical real-world versions of the tasks utilised throughout this thesis.

Appendix A Model Notation for All Analyses

Chapter 2

Chapter 2 – Experiment 1, Response Accuracy

$$
\begin{aligned}
&\mathrm{ACCURACY}_i \sim \mathrm{Bernoulli}(p_i)\\
&\quad \mathrm{logit}(p_i) = \beta_{0j[i]} + \beta_{1j[i]}(\mathrm{TARGET\_FACING\_CAMERA}_i) + \beta_2(\mathrm{PREVALENCE}_{2M1}) + \beta_3(\mathrm{PRESENCE}_{2M1}) + \beta_4(\mathrm{PREVALENCE} \times \mathrm{PRESENCE})_i\\
&\quad \begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} \sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma}\right)\\
&\quad\quad \mathbf{\Sigma} = \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix}\\
&\quad\quad\quad \text{for PPT\_ID} j = 1, \ldots, 53
\end{aligned}
$$

Chapter 2 – Experiment 1, Response Time

$$
\begin{aligned}
&\mathrm{LOG\_RT}_i \sim N(\mu_i, \sigma^2)\\
&\quad \mu_i = \beta_{0j[i]} + \beta_{1j[i]}(\mathrm{TARGET\_FACING\_CAMERA}_i) + \beta_2(\mathrm{PREVALENCE}_{2M1}) + \beta_3(\mathrm{PRESENCE}_{2M1}) + \beta_4(\mathrm{PREVALENCE} \times \mathrm{PRESENCE})_i\\
&\quad \begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} \sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma}\right)\\
&\quad\quad \mathbf{\Sigma} = \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix}\\
&\quad\quad\quad \text{for PPT\_ID} j = 1, \ldots, 53
\end{aligned}
$$

Chapter 2 – Experiment 1, Proportion of Faces Uncovered

$$\text{PROP\_EXTRA\_FACES\_REVEALED}_i \sim \text{ZOIB}(\mu_i, \phi, \alpha, \gamma)$$
$$\text{logit}(\mu_i) = \beta_{0j[i]} + \beta_{1j[i]}(\text{TARGET\_FACING\_CAMERA}_i) + \beta_2(\text{PREVALENCE}_{2M1}) + \beta_3(\text{PRESENCE}_{2M1}) + \beta_4(\text{PREVALENCE} \times \text{PRESENCE})_i$$
$$\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} \sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma}\right)$$
$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix}$$
$$\text{for PPT\_ID} j = 1, \ldots, 53$$

Chapter 2 – Experiment 1, Average Speed

$$\text{AVG\_SPEED}_i \sim N(\mu_i, \sigma^2)$$
$$\mu_i = \beta_{0j[i]} + \beta_{1j[i]}(\text{TARGET\_FACING\_CAMERA}_i) + \beta_2(\text{PREVALENCE}_{2M1}) + \beta_3(\text{PRESENCE}_{2M1}) + \beta_4(\text{PREVALENCE} \times \text{PRESENCE})_i$$
$$\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} \sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma}\right)$$
$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix}$$
$$\text{for PPT\_ID} j = 1, \ldots, 53$$

Chapter 2 – Experiment 2, Response Accuracy

$$
\begin{aligned}
\mathrm{ACCURACY}_i &\sim \mathrm{Bernoulli}(p_i) \\
\mathrm{logit}(p_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\mathrm{TARGET\_FACING\_CAMERA}_i) + \beta_2(\mathrm{PREVALENCE}_{2M1}) + \beta_3(\mathrm{PRESENCE}_{2M1}) + \beta_4(\mathrm{PREVALENCE} \times \mathrm{PRESENCE})_i \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \ldots, 50
\end{aligned}
$$

Chapter 2 – Experiment 2, Response Time

$$
\begin{aligned}
\mathrm{LOG\_RT}_i &\sim N(\mu_i, \sigma^2) \\
\mu_i &= \beta_{0j[i]} + \beta_{1j[i]}(\mathrm{TARGET\_FACING\_CAMERA}_i) + \beta_2(\mathrm{PREVALENCE}_{2M1}) + \beta_3(\mathrm{PRESENCE}_{2M1}) + \beta_4(\mathrm{PREVALENCE} \times \mathrm{PRESENCE})_i \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \ldots, 50
\end{aligned}
$$

Chapter 2 – Experiment 2, Proportion of Faces Uncovered

$$\begin{aligned}
\mathrm{PROP_EXTRA_FACES_REVEALED}_i &\sim \mathrm{ZOIB}(\mu_i, \phi, \alpha, \gamma) \\
\mathrm{logit}(\mu_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\mathrm{TARGET_FACING_CAMERA}_i) + \beta_2(\mathrm{PREVALENCE}_{2M1}) + \beta_3(\mathrm{PRESENCE}_{2M1}) + \beta_4(\mathrm{PREVALENCE} \times \mathrm{PRESENCE})_i \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for } \mathrm{PPT_ID} j = 1, \ldots, 50
\end{aligned}$$

Chapter 2 – Experiment 2, Average Speed

$$\begin{aligned}
\mathrm{AVG_SPEED}_i &\sim N(\mu_i, \sigma^2) \\
\mu_i &= \beta_{0j[i]} + \beta_{1j[i]}(\mathrm{TARGET_FACING_CAMERA}_i) + \beta_2(\mathrm{PREVALENCE}_{2M1}) + \beta_3(\mathrm{PRESENCE}_{2M1}) + \beta_4(\mathrm{PREVALENCE} \times \mathrm{PRESENCE})_i \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for } \mathrm{PPT_ID} j = 1, \ldots, 50
\end{aligned}$$

Chapter 2 – Proportion of Faces Uncovered, Experiments Combined

$$\begin{aligned}
\mathrm{PROP_EXTRA_FACES}_i &\sim \mathrm{ZOIB}(\mu_i, \phi, \alpha, \gamma) \\
\mathrm{logit}(\mu_i) &= \beta_{0j[i]} + \beta_1(\mathrm{PREVALENCE}_{2-1}) + \beta_2(\mathrm{Experiment}_{2-1}) + \beta_3(\mathrm{PREVALENCE}_{2-1} \times \mathrm{Experiment}_{2-1}) \\
\beta_{0j} &\sim N(\mu_{\beta_0}, \sigma_{\beta_0}^2) \\
&\text{for } \mathrm{PPT_ID} j = 1, \ldots, 103
\end{aligned}$$

Chapter 3

Chapter 3 – Experiment 1, First Interaction Choice

$$
\begin{aligned}
\text{EFFORT\_TYPE\_BINOMIAL}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \ldots, 40
\end{aligned}
$$

Chapter 3 – Experiment 1, Second Interaction Choice

$$
\begin{aligned}
\text{EFFORT\_TYPE\_BINOMIAL\_SECOND}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{CLOSEST\_LOW}_{2M1}) \\
&\quad + \beta_4(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) + \beta_5(\text{PRESENCE}_{2M1} \times \text{CLOSEST\_LOW}_{2M1}) \\
&\quad + \beta_6(\text{SCALED\_INDEX}_i \times \text{CLOSEST\_LOW}_{2M1}) \\
&\quad + \beta_7(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i \times \text{CLOSEST\_LOW}_{2M1}) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \ldots, 40
\end{aligned}
$$

Chapter 3 – Experiment 1, Number of Faces Viewed

$$
\begin{aligned}
\text{TOTAL\_FACES\_VIEWED}_i &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{EFFORT\_TYPE}_{2M1}) \\
&\quad + \beta_4(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) + \beta_5(\text{PRESENCE}_{2M1} \times \text{EFFORT\_TYPE}_{2M1}) \\
&\quad + \beta_6(\text{SCALED\_INDEX}_i \times \text{EFFORT\_TYPE}_{2M1}) \\
&\quad + \beta_7(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i \times \text{EFFORT\_TYPE}_{2M1}) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \dots, 40
\end{aligned}
$$

Chapter 3 – Experiment 2, First Interaction Choice

$$
\begin{aligned}
\text{INFORMATION\_TYPE\_BINOMIAL}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \dots, 45
\end{aligned}
$$

Chapter 3 – Experiment 2, Second Interaction Choice

$$
\begin{aligned}
\text{INFO\_BINOMIAL\_SECOND}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{CLOSEST\_HIGH}_{2M1}) \\
&\quad + \beta_4(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) + \beta_5(\text{PRESENCE}_{2M1} \times \text{CLOSEST\_HIGH}_{2M1}) \\
&\quad + \beta_6(\text{SCALED\_INDEX}_i \times \text{CLOSEST\_HIGH}_{2M1}) \\
&\quad + \beta_7(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i \times \text{CLOSEST\_HIGH}_{2M1}) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \boldsymbol{\Sigma} \right) \\
\boldsymbol{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \ldots, 45
\end{aligned}
$$

Chapter 3 – Experiment 2, Number of Faces Viewed

$$
\begin{aligned}
\text{TOTAL\_FACES\_VIEWED}_i &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{INFORMATION\_TYPE}_{2M1}) \\
&\quad + \beta_4(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) + \beta_5(\text{PRESENCE}_{2M1} \times \text{INFORMATION\_TYPE}_{2M1}) \\
&\quad + \beta_6(\text{SCALED\_INDEX}_i \times \text{INFORMATION\_TYPE}_{2M1}) \\
&\quad + \beta_7(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i \times \text{INFORMATION\_TYPE}_{2M1}) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \dots, 45
\end{aligned}
$$

Chapter 3 – Experiment 2, Time to Stop Following Reveal of Information

$$
\begin{aligned}
\text{LOG\_TIME\_TO\_STOP}_i &\sim N(\mu_i, \sigma^2) \\
\mu_i &= \beta_{0j[i]} + \beta_{1j[i]}(\text{PRESENCE}_{2M1}) + \beta_2(\text{SCALED\_INDEX}_i) + \beta_3(\text{PRESENCE}_{2M1} \times \text{SCALED\_INDEX}_i) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{pmatrix} \gamma_0^{\beta_0} \\ \gamma_1^{\beta_1} \end{pmatrix}, \mathbf{\Sigma} \right) \\
\mathbf{\Sigma} &= \begin{pmatrix} \sigma_{\beta_0}^2 & \rho\sigma_{\beta_0}\sigma_{\beta_1} \\ \rho\sigma_{\beta_0}\sigma_{\beta_1} & \sigma_{\beta_1}^2 \end{pmatrix} \\
&\text{for PPT\_ID} j = 1, \dots, 45
\end{aligned}
$$

Chapter 4

Chapter 4 – Experiment 1, Probability of Selecting Coin as First Interaction

$$
\begin{aligned}
\text{INTERACTED\_WITH\_FIRST}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_1(\text{COIN\_TYPE}_{2M1}) \\
\beta_{0j} &\sim N\left(\gamma_0^{\beta_0}, \sigma^2_{\beta_{0j}}\right) \\
&\text{for PPT\_ID}j = 1, \dots, 38
\end{aligned}
$$

Chapter 4 – Experiment 1, Probability of Selecting Coin as Second Interaction

$$
\begin{aligned}
\text{INTERACTED\_WITH\_SECOND}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_1(\text{COIN\_TYPE}_{2M1}) + \beta_2(\text{PREV\_OBJECT\_TYPE}_{2M1}) \\
&\quad + \beta_3(\text{COIN\_TYPE}_{2M1} \times \text{PREV\_OBJECT\_TYPE}_{2M1}) \\
\beta_{0j} &\sim N\left(\gamma_0^{\beta_0}, \sigma^2_{\beta_{0j}}\right) \\
&\text{for PPT\_ID}j = 1, \dots, 38
\end{aligned}
$$

Chapter 4 – Experiment 1, Total Coins Flipped

$$
\begin{aligned}
\text{TOTAL\_FLIPS\_PER\_COIN}_i &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \beta_{0j[i]} + \beta_1(\text{PRESENCE}_{2M1}) + \beta_2(\text{COIN\_TYPE}_{2M1}) + \beta_3(\text{PRESENCE}_{2M1} \times \text{COIN\_TYPE}_{2M1}) \\
\beta_{0j} &\sim N\left(\gamma_0^{\beta_0}, \sigma^2_{\beta_{0j}}\right) \\
&\text{for PPT\_ID} j = 1, \ldots, 38
\end{aligned}
$$

Chapter 4 – Experiment 2, Probability of Selecting Coin as First Interaction

$$
\begin{aligned}
\text{INTERACTED\_WITH\_FIRST}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_1(\text{TIME\_GROUP}_{2M1}) + \beta_2(\text{COIN\_TYPE}_{2M1}) \\
&\quad + \beta_3(\text{TIME\_GROUP}_{2M1} \times \text{COIN\_TYPE}_{2M1}) \\
\beta_{0j} &\sim N\left(\gamma_0^{\beta_0}, \sigma^2_{\beta_{0j}}\right) \\
&\text{for PPT\_ID} j = 1, \ldots, 40
\end{aligned}
$$

Chapter 4 – Experiment 2, Probability of Selecting Coin as Second Interaction

$$
\begin{aligned}
\text{INTERACTED\_WITH\_SECOND}_i &\sim \text{Bernoulli}(p_i) \\
\text{logit}(p_i) &= \beta_{0j[i]} + \beta_1(\text{TIME\_GROUP}_{2M1}) + \beta_2(\text{COIN\_TYPE}_{2M1}) + \beta_3(\text{PREV\_OBJECT\_TYPE}_{2M1}) \\
&\quad + \beta_4(\text{TIME\_GROUP} \times \text{COIN\_TYPE}) + \beta_5(\text{TIME\_GROUP} \times \text{PREV\_OBJECT}) \\
&\quad + \beta_6(\text{COIN\_TYPE} \times \text{PREV\_OBJECT}) + \beta_7(\text{TIME\_GROUP} \times \text{COIN\_TYPE} \times \text{PREV\_OBJECT}) \\
\beta_{0j} &\sim N\left(\gamma_0^{\beta_0}, \sigma^2_{\beta_{0j}}\right) \\
&\text{for PPT\_ID} j = 1, \ldots, 36
\end{aligned}
$$

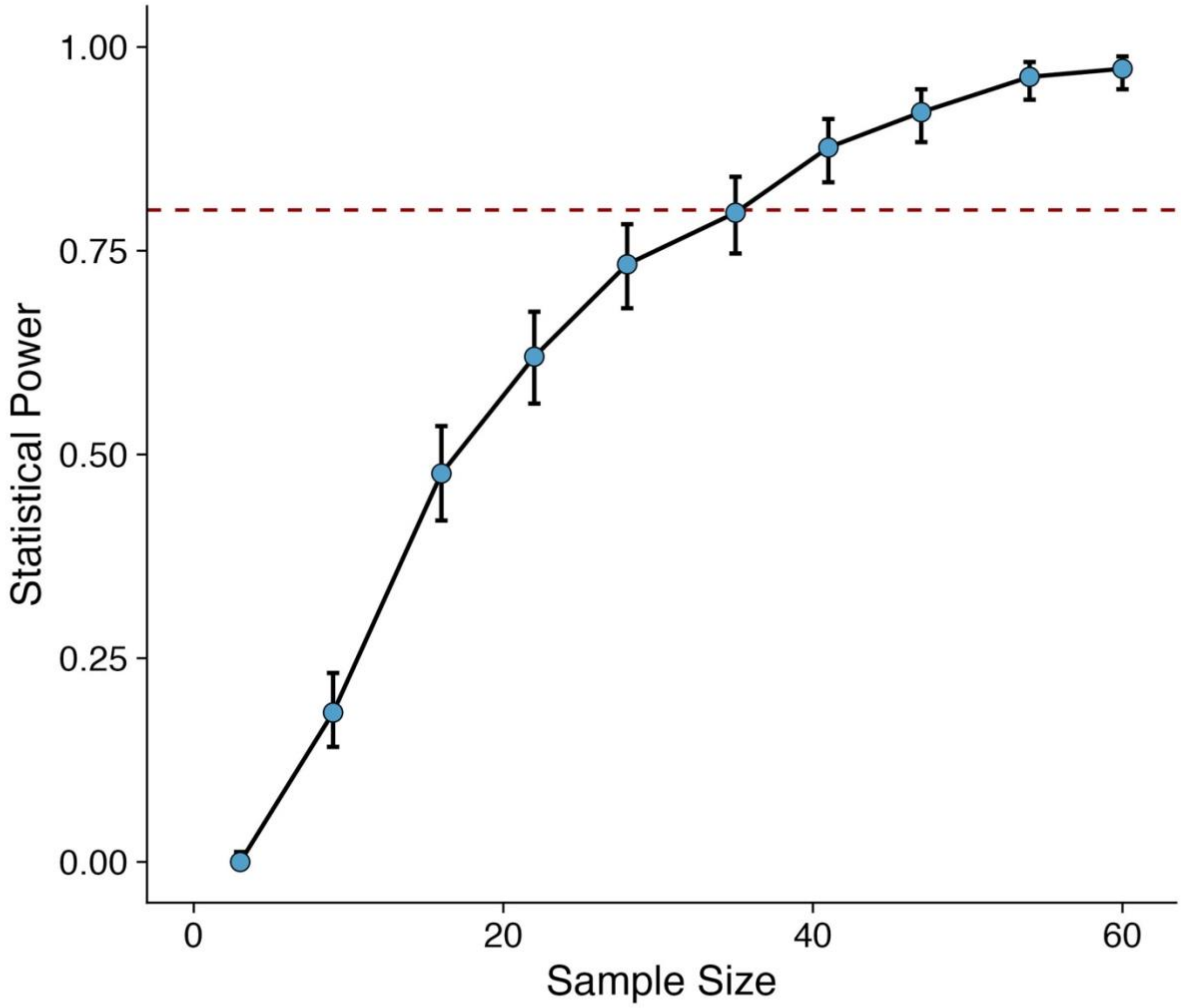
Chapter 4 – Experiment 2, Total Coins Flipped

$$
\begin{aligned}
\text{TOTAL\_FLIPS\_PER\_COIN}_i &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \beta_{0j[i]} + \beta_1(\text{PRESENCE}_{2M1}) + \beta_2(\text{COIN\_TYPE}_{2M1}) + \beta_3(\text{TIME\_GROUP}_{2M1}) \\
&\quad + \beta_4(\text{PRESENCE} \times \text{COIN\_TYPE}) + \beta_5(\text{PRESENCE} \times \text{TIME\_GROUP}) \\
&\quad + \beta_6(\text{COIN\_TYPE} \times \text{TIME\_GROUP}) + \beta_7(\text{PRESENCE} \times \text{COIN\_TYPE} \times \text{TIME\_GROUP}) \\
\beta_{0j} &\sim N\left(\gamma_0^{\beta_0}, \sigma^2_{\beta_{0j}}\right) \\
&\text{for PPT\_ID} j = 1, \ldots, 40
\end{aligned}
$$

Appendix B Power Plots for SIMR Power Analyses

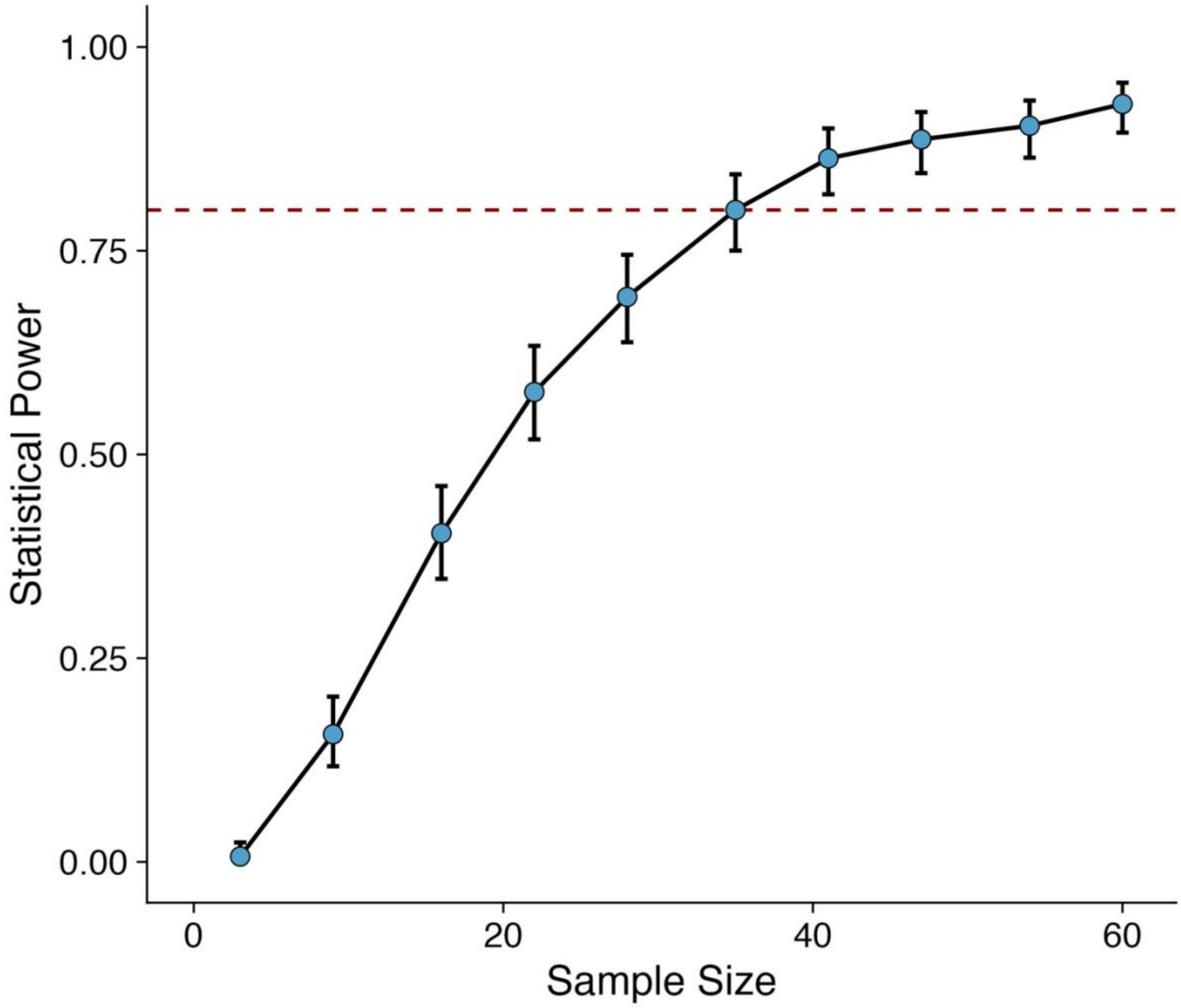
Chapter 2 Power Analyses

Experiment 1 Power Curve



Note. Power analysis for response accuracy. Dashed line depicts 80% power. X-axis depicts required number of participants.

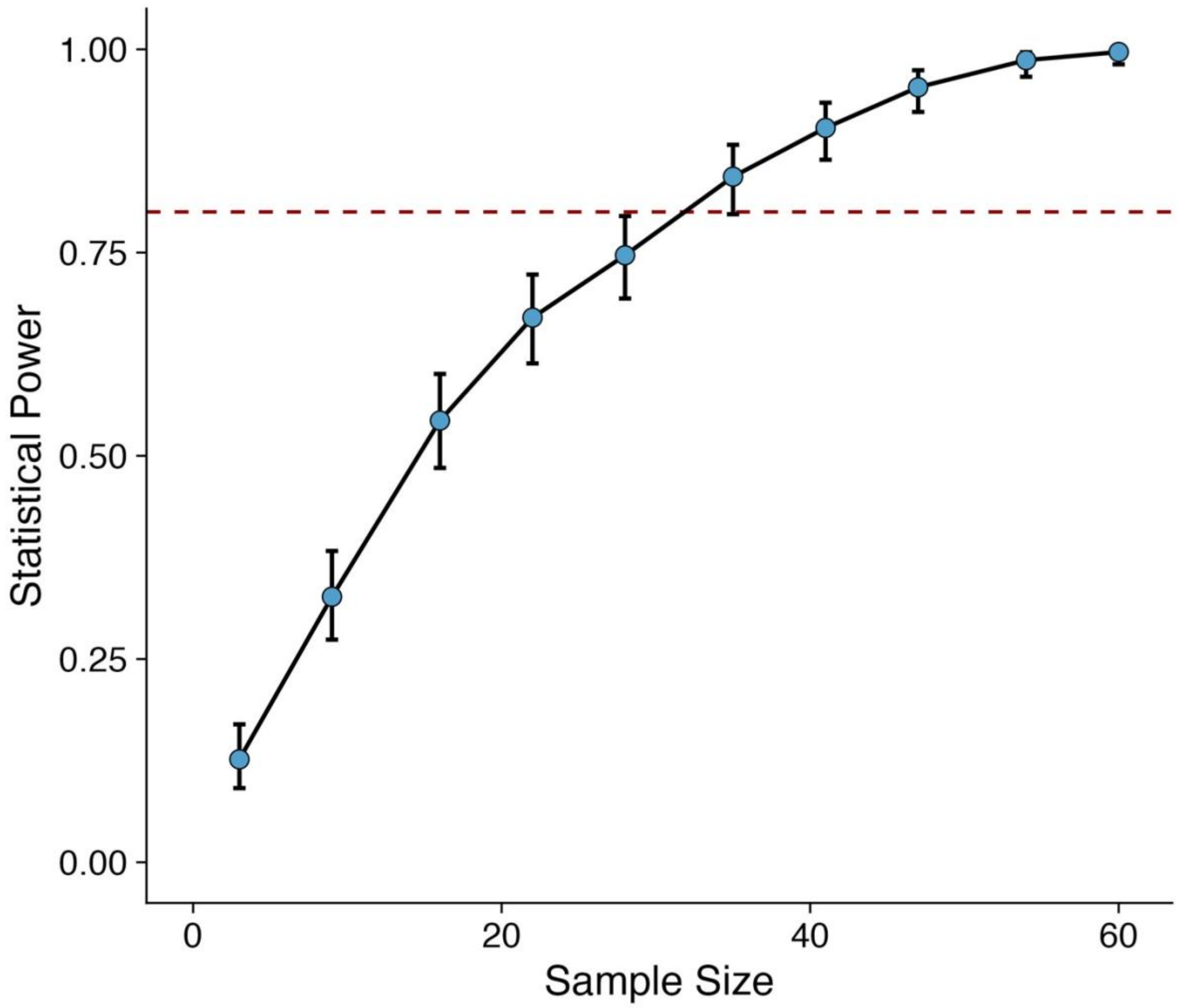
Experiment 2 Power Curve



Note. Power analysis for response accuracy. Dashed line depicts 80% power. X-axis depicts required number of participants.

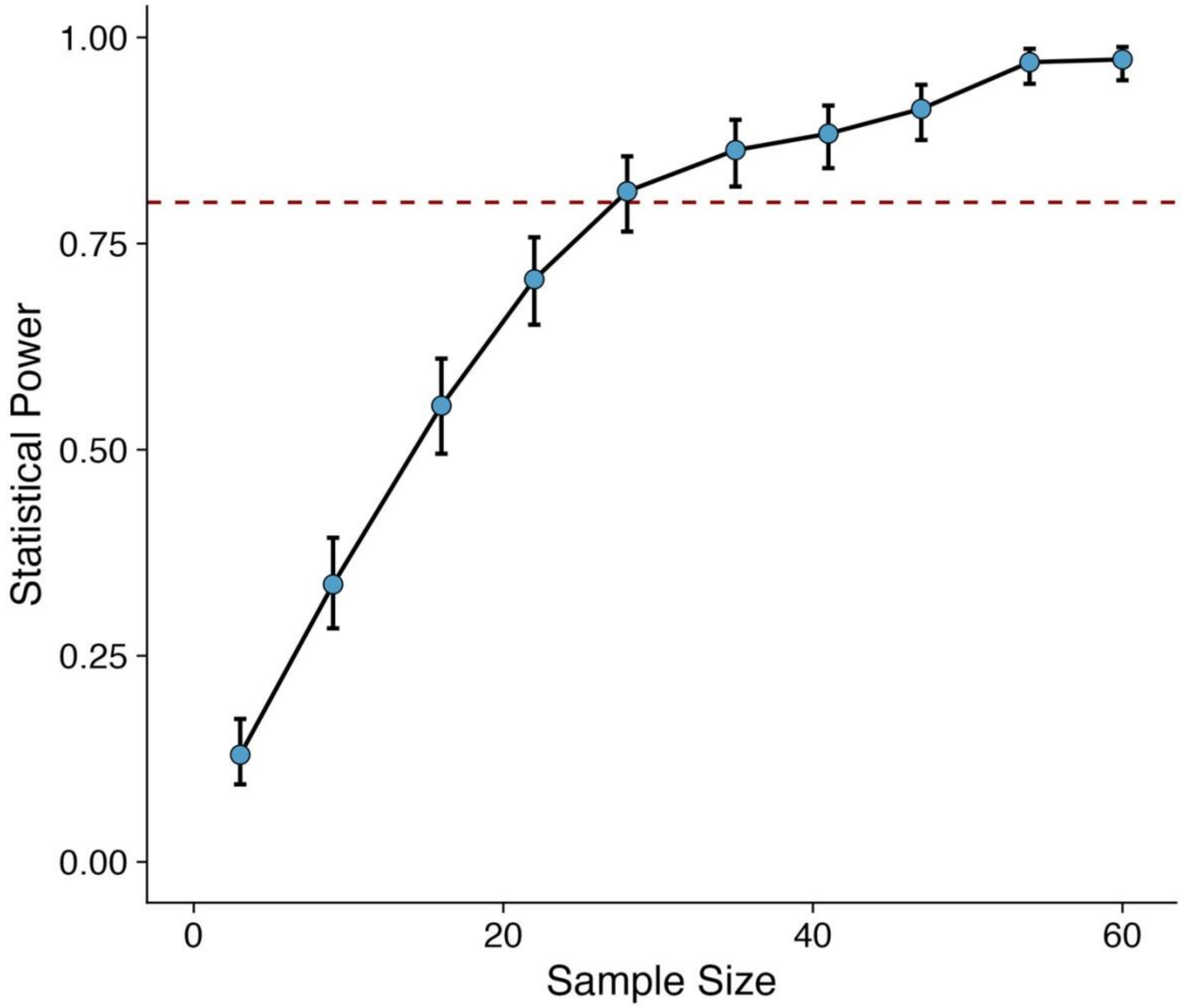
Chapter 3 Power Analyses

Experiment 1 Power Curve



Note. Power analysis for first interaction choice. Dashed line depicts 80% power. X-axis depicts required number of participants.

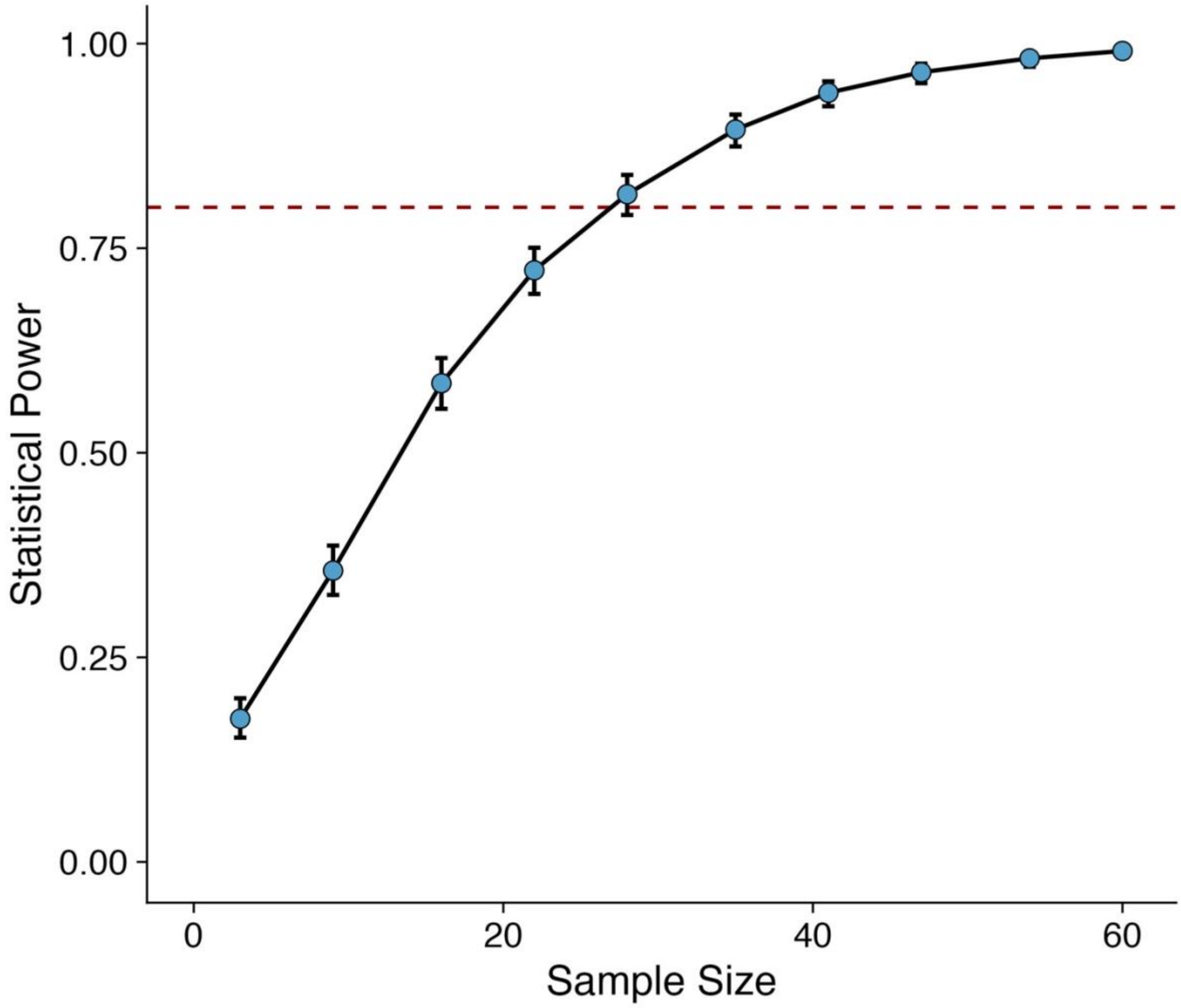
Experiment 2 Power Curve



Note. Power analysis for first interaction choice. Dashed line depicts 80% power. X-axis depicts required number of participants.

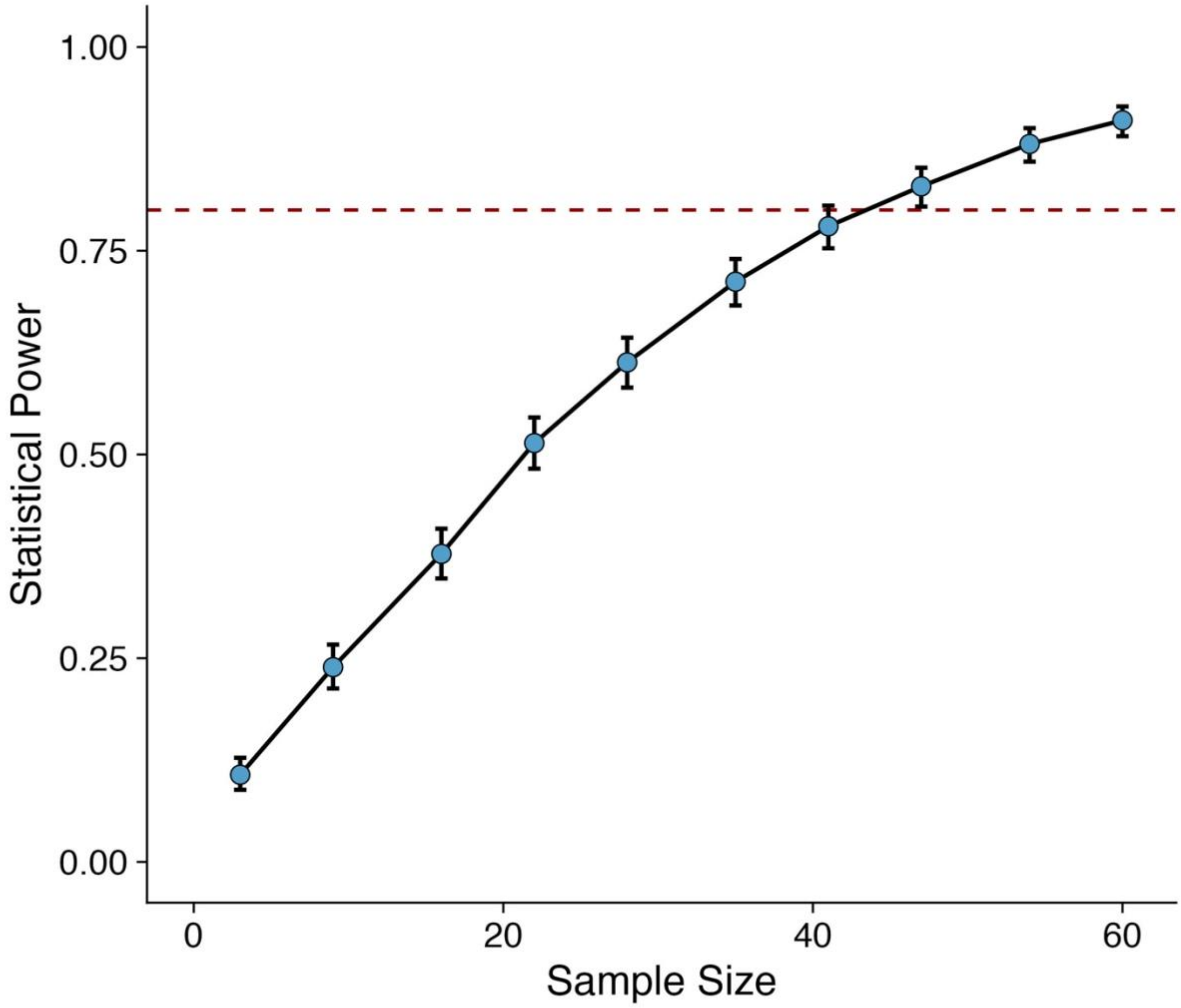
Chapter 4 Power Analyses

Experiment 1 Power Curve



Note. Power analysis for first interaction choice. Dashed line depicts 80% power. X-axis depicts required number of participants.

Experiment 2 Power Curve



Note. Power analysis for first interaction choice. Dashed line depicts 80% power. X-axis depicts required number of participants.

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