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Designing Better Symbols: An Attentional Approach to Match Symbols to Performance Goals

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Preface

The following thesis is intended for publication. The initial idea for the project described in this thesis was by Dr. Kelly Steelman. The data collection and analyses in Chapters, 3, 4 and 5 are my original work under the guidance of Dr. Kelly Steelman. I wrote the manuscript under the careful review of Dr. Kelly Steelman.

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Abstract

Effective displays require symbol sets that are customized to specific tasks and performance goals. In order to create such sets, designers must account for the effects of top-down and bottom-up attention. The current work presents a pair of experiments that examined the effects of salience and cueing in a change detection tasks within the flicker paradigm (Rensink, O'Regan and Clark, 1997). Each trial, participants either received no cue or a cue indicating which symbol would be the target. This cueing manipulation isolated top-down effects to the cued condition. Consistent with previous studies (Orchard, 2012; Steelman, Orchard, Fletcher, Cockshell, Williamson & McCarley, 2013), Study 1 found a response time benefit for low salience symbols in the cued condition. Study 2 served as a replication of Study 1, but included a background manipulation that preserved the layout of the symbols while manipulating the symbol's contrast to the background color. Results indicated a benefit for low salience symbols in the cued condition only on the black background, consistent with Study 1. However, low salience symbols showed no benefit on the gray or the white background in the cued condition, failing to support the hypothesis that low salience symbol show a cueing benefit. Chapter 5 conducted an extended analysis of the data from Study 2 using a variety of multilevel models to investigate specific symbol characteristics that may drive response times. For both uncued and cued search, eccentricity and crowding effects predicted response times. For uncued search, response times decreased as salience increased and standard deviation increased. For cued search symbol discriminability and salience predicted response times. Implications for the design of symbols and symbol sets are discussed.

Chapter 1: Introduction

The design of effective displays requires a symbol set customized to specific tasks and performance goals. For example, to increase the likelihood that a symbol will be found quickly a symbol should be both discriminable from other symbols and discriminable from the background. Not all tasks, however, require rapid detection of all symbols. In some cases, we may want to prioritize the detection of a single symbol (e.g., dangerous object). In others, we may want all symbols to be found equally efficiently. In order to design symbol sets that facilitate particular tasks and performance goals we must consider the two attentional mechanisms that drive our search behaviors.

The mechanisms that guide our visual attention are grouped into two categories: bottom-up and top-down. Bottom-up processes bias our attention toward salient features within an image including color, contrast, luminance, motion and brightness (Itti & Koch, 2001). Since salience is dependent on the surroundings, a symbol that is salient in one context may not be salient in another. Top-down processes, in contrast, bias our attention toward features of potential importance or high expectancy (Yarbus, 1967; Wolfe, 1994, Connor, Egeth, & Yantis, 2004). Feature guidance, one form of top-down control, guides attention towards specific properties of an object such as color and shape. The guidance by feature, specifically color, was the focus of the main study.

Although the bottom-up and top-down processes are clearly defined, their exact relationship is not fully understood (Van der Stichgel, 2009). Some studies suggest a dominant role of top-down mechanisms, mainly in goal-directed tasks or tasks with

"The material contained in this chapter is in preparation for submission to a journal".

naturalistic images (Bacon & Egeth, 1997; Foulsham & Underwood, 2011), whereas other studies demonstrate that salience may override top-down goals (Theeuwes, 1991). Yet other studies suggest that bottom-up and top-down mechanisms interact in specific ways (Wolfe, 1994). It is difficult, however, to determine whether top-down or bottom-up factors are guiding attention. In many cases, the regions that are the most important for a task may also be the most salient ones (McCarley, Steelman, & Horrey, 2014).

Disentangling the effects of top-down and bottom-up processes requires a paradigm that isolates the effects and a reliable measure of salience. Steelman, Orchard, Fletcher, Cockshell, Williamson and McCarley (2013) developed such a task using a cueing manipulation within the flicker-paradigm. Target-absent and target-present images, separated by a blank screen, are cycled through to create a “flicker” that masks the onset and the offset of the target. Participants’ task is to find the symbol that is appearing and disappearing within that flicker. Participants either received no cue or a cue indicating which symbol would be the target. This manipulation isolated top-down effects to the cued condition. In the uncued condition, salience alone should guide attention, as participants did not know the target’s identity. In this study, salience was measured using the Saliency Toolbox (Walther & Koch, 2006). Results showed faster response times for high salient symbols in the uncued condition, indicating the guidance by salience. However, in the cued condition results showed an unexpected benefit for low salient symbols, suggesting that top-down search may inhibit bottom-up control.

The current study seeks to replicate this effect and identify the mechanisms that may drive it. To disentangle the effects of bottom-up and top-down mechanisms the study used the same paradigm as Steelman et al. (2013). Salience was measured using the Saliency Toolbox (Walther & Koch, 2006).

Study 1 served as a pilot study to replicate the effects from Steelman et al. (2013) using a custom symbol set that I designed using specific salience characteristics. Based on previous studies, I expected high salience symbols to be detected faster in the uncued condition, whereas in the cued condition, I expected a response time benefit for low salience symbols based on the results from Steelman et al. (2013). Results confirmed these expectations, successfully replicating the effect for low salience symbols in the cued condition.

Study 2 used the same paradigm as Study 1, but added a background manipulation that preserved the layout of the symbols while manipulating the symbol's contrast to the background color. This background manipulation varied each symbol's salience. Results indicated a benefit for low salience symbols in the cued condition only on the black background, which aligns with the findings from Study 1 and Steelman et al. (2013). However, low salience symbols showed no benefit on the gray or the white background in the cued condition, contradicting with the existence of the low salience symbol benefit.

Chapter 5 conducted an extended analysis of the data from Study 2 with the goal to investigate specific symbol characteristics that may drive the cueing effects observed in the studies. The overall goal was to identify and characterize the factors that make a symbol a good cue. These factors can then be used to help develop design guidelines that support specific tasks and performance goals.

Chapter 2: Literature Review

A sign is "something which represents or signifies an object to some interpretant" (Peirce, 1902). In the late 19^{th} century the philosopher Charles S. Peirce distinguished between three kinds of signs: the icon, the index and the symbol. An icon physically resembles the object that it stands for. For example, the picture of a hospital may represent an actual hospital on an emergency map. In contrast, a symbol is an arbitrary or abstract object that has assigned meaning to it, which needs to be learned. For example, in the military a yellow clover represents an unknown entity and a blue horseshoe represents a friend. This manuscript focuses on symbols rather than icons.

Existing symbol standards provide guidelines for designing symbols (Dymon, 2003), but give little advice on how to assemble the overall symbol set. Since one symbol within a set affects all the other symbols, having guidelines for symbol sets is very important.

Standards for Designing Symbols

Numerous organizations provide symbol standards and design guidelines. The Department of Homeland Security (DHS) provides standards for emergency maps (ANSI, 2006; Martin & Black, 2007) that specify design requirements for point symbol markers and style guidelines for boundary lines (Kostelnick et al., 2008). The Department of Defense (D.O.D), on the other hand, provides symbol standards for military operations (MIL-STD, D. O. D., 2008).

"The material contained in this chapter is in preparation for submission to a journal".

The ANSI 415-2006 INCITS standard requires pictograms in emergency maps to facilitate the immediate response to an event (Cutter, 2003). The symbols need to convey important information quickly in high stress or pressure situations such as natural disasters, fires, and terrorist attacks. As part of the design process, the ANSI symbols were tested on workers of the public sector like fire fighters, first responders, and emergency managers in an online survey (fgdc.gov/HSWG/index.html). Participants were provided with a symbol and the meaning and had to either accept or reject the symbol and its definition. A separate comment section allowed them to make suggestions to improve the design. An acceptance rate for a symbol of 75% or higher was required to be implemented in the symbol set; otherwise symbols were reviewed and redesigned. Although the ANSI standard was tested before implementation, this particular test may be insufficient for guaranteeing that symbols will be interpreted correctly. After all, participants only had to accept the symbol –definition pairs; they did not need to guess the symbol meaning based on the symbol's appearance alone. In fact, a later study asked 50 firefighters whether they could identify the meaning of the 28 fire-related symbols and how they would respond to the symbols. Results showed that only 6 (out of 28) of the fire-related symbols were fully comprehended and achieved the required 75% quality rate (Akella, 2009).

In addition to failing to achieve the required quality rate for most symbols, the symbol set was not tested as a whole. The previous studies did not examine whether symbols within the set could be easily discriminated from one another. Thus, even though the tests determined whether or not a symbol achieved the specified quality benchmark, they did not test if the symbols would support the users' performance goals and specific task requirements.

Not all symbol sets use pictograms, however, some use abstract symbols with meaning assigned to them. The military, for example, uses abstract symbols to represent enemies, friends and unknown entities in their standard the MIL-STD-2525B and the newer version MIL-STD-2525C (MIL-STD2525C, D. O. D., 2008). An extract of both sets is depicted in Figure 1. The design of the symbols in this case is important to promote the military's performance goals. A specific performance goal may be the rapid detection of a hostile or unknown symbol since they can potentially represent danger. In this case, rapid detection of a hostile entity (red house) may be more important than an assumed friend (blue horseshoe).

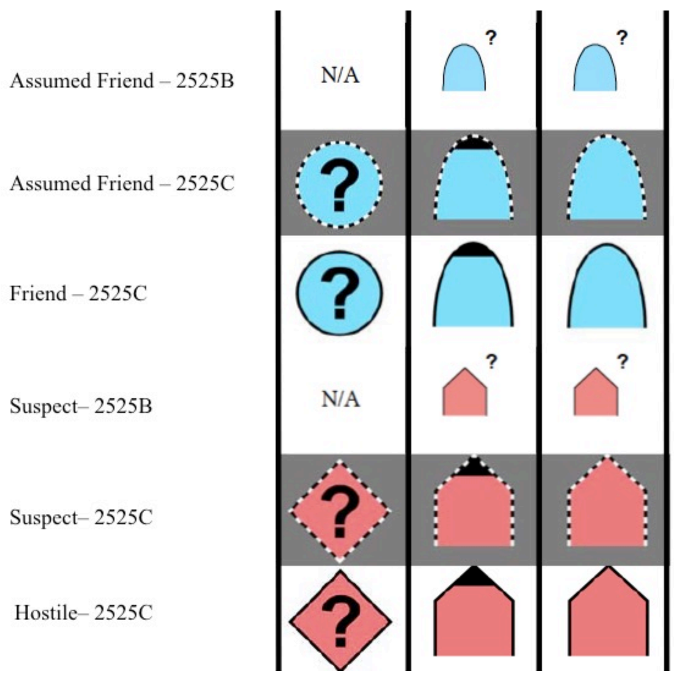

Figure 1. Extract of symbols from the MIL-STD-2525B and MIL-STD-2525C (see Appendix A, http://www.dtic.mil/dtic/).

Some researchers have questioned if these symbols support ideal search behavior and particular performance goals. Fletcher, Arnold and Cockshell (2011) investigated the accurate and rapid detection of these symbols in a visual search task to see how well they perform, especially in cluttered environments. Participants, employees of the Defense Science and Technology Organization (DSTO) in Australia, received a cue indicating which symbol to look for and had to decide if that symbol was present or absent in each trial. Results indicated significantly longer search times for the friend, assumed friend, suspect and hostile symbols compared to the neutral and unknown symbol for the MIL-STD-2525B. It would seem plausible that operators would want to prioritize suspects and hostile entities over neutral ones. So why might it take longer to find hostile symbols than unknown symbols? One reason may be the symbols are not discriminable enough, which in return did not allow the operator to reduce the search set. For example, the suspect and hostile symbols share the same color and are only distinguished by using a dotted outline. This is also the case for the assumed friend and friend differences; they are both blue with only the dotted outline being different. This small difference may not be enough to allow the operator to restrict his or her search to a specific class of symbols, for example only hostile symbols. Fletcher et al. (2011) also investigated the newer version MIL-STD-2525C. This modified version made small changes to the assumed friend and suspect symbols by adding white into the dashed frame line of the symbols. Results showed that these small changes speeded search times for the suspect and hostile symbols relative to the older MIL-STD-2525B. However, the assumed friend and friend symbols produced poorer search performance than the MIL-STD-2525B, resulting in a higher error rate and higher search times. The results here highlight how important it is to consider not only the design of individual symbols, but the design of the entire set. Further, it is unclear why specific meanings were mapped to specific colors and shapes. To support a specific performance goal, it is therefore important to match entities to goals. For example, the most important entity should be deliberately assigned to the symbol that supports the most rapid detection.

Change Detection

Fletcher et al. (2011) used a visual search task to highlight differences in search efficiency. Not all tasks require the operator to search for a pre-specified target. Military operators, for example, engage in supervisory monitoring tasks, in which they monitor and track objects on displays. They are not searching for a specific target, but are expected to notice changes or the appearance of new entities on the screen. Change detection can be incredibly difficult particularly when the change occurs when attention is diverted or the change is occluded by another object or within a blink or saccade. For example, the military operator who completes supervisory monitoring tasks may have to focus his or her attention on one or more displays. If he or she looks away for a brief moment or blinks, he or she might miss the onset of an object. This difficulty detecting changes is termed change blindness and is formally defined as the failure to detect changes in objects and scenes due to the momentarily diversion of attention due to observer's blinks or saccades when switching between monitors (Simons & Levin, 1997). As it would be inefficient to time changes with participants' blinks, multiple paradigms have been developed to mask the change and study the factors that may influence change blindness in the lab, for example, the superimposition of a “mud-splash” on the image that is viewed (O’Regan, Rensink, & Clark, 1999) or a flicker that uses a blank interval between an original image and modified version (Rensink, O’Regan, & Clark, 1997). This flicker paradigm was used to investigate the ability of operators from the Space and Naval Warfare System to detect task-relevant changes when monitoring multiple displays (DiVita, Obermayer, Nugent, & Nashville, 2004). Results showed that change blindness occurs even when monitoring displays with only 8 items. Notably, change blindness can not only occur when monitoring a few objects, it also occurs when participants are highly familiar with a scene. Henderson and Hollingworth (1999) illustrated change blindness by instructing participants to look for changes in naturalistic color images. These changes occurred during a saccade or a blink, but participants still failed to notice changes even though they were told to memorize the scene.

The failure to notice changes shows just how important it is to ensure that operators can quickly and easily detect objects. However, to create symbol sets that support these specific performance goals, one needs an understanding of the attentional mechanisms that guide our attention.

Attentional Mechanisms

To design symbol sets that match performance goals we need to understand the two attentional processes that guide our attention. Bottom-up processes bias our attention toward salient features within an image (Itti & Koch, 2000), including color, contrast, luminance, motion and brightness (Itti & Koch, 2001). Top-down processes, in contrast, bias our attention toward features of potential importance or high expectancy (Yarbus, 1967; Wolfe, 1994, Connor, Egeth, & Yantis, 2004).

Bottom-Up Processes

Bottom-up processes can shift our attention involuntarily towards visually salient features based upon raw sensory input (Connor, Egeth, & Yantis, 2004). The term visually salient refers to distinctiveness or contrast in features like color, contrast, luminance, motion and brightness (Itti & Koch, 2001). Some features may guide our attention more easily than others. For example, when we search for a red symbol, it may easily stand out against a white background. However, since salience is dependent on the surrounding environment, an object that is salient in one context might not be salient in another (Wolfe & Horrowitz, 2004). Environment in this case may mean an object's background. For example, finding that red symbol on a magenta background will be more difficult than on the white background. Environment, however, may also refer to an object's surroundings including other objects within the same image. Targets that share more than a single property with the distractors such as shape, color, orientation or size show an increased search time (Treisman & Gelade, 1980). For example, if our red symbol is placed among magenta distractors, it will be more difficult to find than if it were placed among green distractors. The amount of similar distractors also plays an important role. The more distractors are surrounding the target, the longer it may take to find the target (Tresiman & Souther, 1985).

However, the color and the number of distractors are not the only important features that capture our attention and influence search times. Yantis and Jonides (1984) proposed luminance to be an important factor when detecting new objects, but later studies showed no benefit for luminance to attract attention (Yantis & Gibson, 1994; Gellatly & Cole, 2000). The onset of a new object itself, however, captured people's attention, independently from a luminance increment (Hillstrom & Yantis, 1994). A more recent study by Franconeri, Hollingworth and Simons (2005) investigated whether the onset of new objects captures attention or rather the transients (e.g., motion and looming) that these new objects create. In a set of experiments a new object was added to a display while a ring-shaped object passed in front (occlusion) or behind (control condition) the array. Results showed a search priority for new objects only in the control condition, indicating evidence for the transient hypotheses. These transients include changes in brightness (Enns, Austen, Di Lollo, Rauschenberger, & Yantis, 2001) and rapid motion (Abrams & Christ, 2003).

Although these bottom-up factors may strongly influence attention capture and search time in some tasks, other tasks may be strongly influenced by the knowledge and experience of the viewer.

Top-Down Processes

Top-down mechanisms bias our attention toward things we learned, know or expect using long-term cognitive strategies (Connor, Egeth, & Yantis, 2004).

Feature guidance, one form of top-down control, can help us guide our attention towards specific features of an object such as color, shape, orientation or size (Wolfe & Horrowitz, 2004). Out of these features color seems to facilitate guidance the most (Hamker, 2004; Wolfe & Horrowitz, 2004). If we are searching for a specific symbol, for example, the hostile symbol, knowing that it is red may help us find it faster. Orchard (2012) compared detection performance involving 4 symbol sets, including 3 that distinguished targets using color and shape and a grayscale set using only different shapes. Orchard found faster detection times for colored symbol sets than grayscale sets, especially when participants were cued and knew what symbol to look for. Symbols that varied in color were better cues that reduced the search set. This reduced functional set leads to a faster detection of the target (Wolfe, Alvarez, Rosenholtz, Kuzmova, & Sherman, 2011).

In addition to feature guidance, spatial expectancy may bias our attention towards locations with a high probability of containing the target (Geng & Behrmann, 2005). In our example, we might expect a red hostile symbol to show up on a specific route or at specific times. Another form of expectancy is contextual cueing (Chung and Jiang, 1998), which is based on the implicit learning of associations between context and a target's location. Thus, our attention is guided towards task-relevant aspects of a scene by our implicit memory. Brockmole and Henderson (2006) showed this effect in realistic images. Participants' search time for a randomly placed target within a scene-image decreased with repetition as their ability to form scene-target associations increased.

These findings suggest that the semantic meaning and memory of a scene facilitate cueing.

Although, thus far bottom-up and top-down have been discussed as separate mechanisms, to be able to effectively create symbols and symbol sets that support specific performance goals, it is crucial to not only understand the top-down and bottom-up mechanisms that may drive performance, but also how they may interact.

Bottom-Up and Top-Down Interaction

Unfortunately, the exact relationship between top-down and bottom-up is not clearly understood (Van der Stichgel, 2009). Some studies suggest a dominant role of top-down mechanisms (Bacon, Egeth, 1997); others claim bottom-up control is dominant (Theeuwes, 1991) and yet others suggest they interact in specific ways (Connor et al., 2004; Wolfe, 1994).

Stirk and Underwood (2007) suggest that top-down factors may override the guidance by salience. In their study, they used photographs showing a variety of indoor scenes such as offices and kitchens as stimuli. A different object of the same size replaced one object within the scene. This object was either scene consistent or inconsistent and of high or low salience. Participants saw two of these photographs separated by a blank screen and had to decide if the images were the same or different. Results showed no difference in detection accuracy and speed for objects of high or low salience. However, inconsistent objects were detected faster than consistent with the scene objects for both high and low salient objects. This study provides evidence for dominant top-down factors that may override the guidance by salience.

On the other hand salient distractors can interfere with goals leading to longer search times, indicating that top-down mechanisms do not always override bottom-up mechanisms (Theeuwes, Kramer, Hahn, & Irwin, 1998). An experiment by Remington, Johnston and Yantis (1992) investigated if task specific goals would override salience. Participants made a two-choice response to a target located in one out of four boxes. Before the target screen, an abrupt-onset visual stimulus was flashed indicating in some trials where the target would appear (same box, different, center, or in all four boxes). In other trials, the onset would appear at nontarget locations. However, the participant was informed of the target-flash relationship before each trial leading to a goal-oriented search. Thus, in some cases participants had to ignore the flash to make the fastest response. Response times, however, indicated that in any case attention was drawn involuntary to the abrupt-onset stimulus. This study provides evidence for strong bottom-up mechanisms regardless of top-down goals.

Although some studies claim that top-down factors are dominant and others claim bottom-up factors are, in many cases it may be difficult to determine whether bottom-up and top-down factors are driving attention. In naturalistic images, it can be especially unclear why people look at certain regions. The regions can be salient or meaningful or the most salient regions might be also the most meaningful (Boyer, Smith, Yu, & Bertenthal, 2011; Foulsham & Underwood, 2011). In traffic, for example, are we looking at a stop sign because it is salient or because it is important or both? McCarley, Steelman and Horrey (2014) investigated this question and showed that the most important information needed to make a decision is often located within salient regions.

Together, these studies demonstrate the difficulty to understand the relationship between top-down and bottom-up mechanisms. Yet, understanding the interplay between these mechanisms is vital for creating useful symbol set design guidelines. Accordingly, one goal of the current project is to carefully control the effects of top-down and bottom-up mechanisms. This requires a paradigm that can isolate the bottom-up and top-down effects and a reliable measure of salience. The following sections introduce several models that can be used to measure salience in an image and a paradigm that successfully isolated top-down and bottom-up factors.

Salience Models

Koch and Ullman (1985) introduced one measure of salience called saliency maps. This two-dimensional map represents the salience of objects on the basis of filters that are tuned to specific features like color, orientation, and contrast. The model then produces an individual saliency map for each feature. These maps then are combined together into an overall saliency map. A winner-take-all principle selects the most salient region in the image.

Since Koch and Ullman first introduced the concept of a saliency map, numerous salience models have been developed and implemented. An up-to-date collection of existing salience models can be found online under saliency.mit.edu. This collection contains 56 different salience models and is still growing. Here, I choose to review four different models based on their easy implementation into Matlab and their available documentation.

Walther (Walther & Koch, 2006) originally created the Saliency Toolbox in the Koch Lab at the Californian Institute of Technology, based upon the previous work of Koch and Ullman. The model is implemented in Matlab and has a graphical user interface making it easy to use for practitioners. The Saliency Toolbox computes and displays a saliency map for any input image and provides eye movements and fixation predictions. The model has been widely used and has been cited over 50 times (saliencytoolbox.net).

The Graph-Based Visual Saliency (GBVS) algorithm (Harel, Koch, & Perona, 2006) was also created in the Koch lab with the goal to create a better and easier version of the Saliency Toolbox (Walther & Koch, 2006). The GBVS model gives higher salience values to objects in the middle of the image, which accounts for eccentricity effects that can typically be found in human data. This model produces its saliency map in two steps. First, activation maps are formed based on specific features such as color, intensity and orientation. Just like in the Saliency Toolbox (Walther & Koch, 2006), these features can be modified and weighted accordingly. The model has been validated in an eye movement study, reliably predicting the salient locations (Harel, Koch, & Perona, 2006). Participant's task was to look for a change in real-world images. The original image and a modified version of it were displayed alternatingly with a mask to hide the change. Results showed that the GBVS model predicted human fixations accurately 98% of the time, compared to a prediction of 84% for the Itti & Koch algorithm.

The Simpsal map (Harel, 2012) is a radically simplified version of the original Itti & Koch algorithm. It excludes the orientation channel and the ability to change the weighing of the maps. It provides researchers with a simple code in Matlab to quickly create a saliency map. This simplified version is faster and more accurate in fixation predictions than the original Itti & Koch algorithm; it only varies slightly in output. However, the GBVS algorithm is more accurate than the simpsal model (Harel, 2012).

Another recent model is the Image Signature model (Sigsal) (Hou, Harel, & Koch, 2012). It uses a binary, holistic image descriptor called image signature to tackle the figure-ground separation problem, which describes the problem of finding objects in a scene and distinguishing them from their background. This descriptor can be used to approximate a sparse foreground, which can be useful to detect salient regions. The saliency algorithm first resizes the input image to a 64 x 48 pixel representation and then creates a saliency map for each of the three color channels (RGB) based on the image signature. The sum across these three channel saliency maps creates the final saliency map. As shown in Hou et al. (2012) the highest salient location calculated by the model was consistent with first fixations.

All these models provide us with reliable measures of salience. However, we still need a paradigm that can isolate top-down and bottom-up effects. The next section will present a paradigm that has successfully isolated top-down factors to one condition.

Disentangling Bottom-Up and Top-Down effects

Steelman, Orchard, Fletcher, Cockshell, Williamson and McCarley (2013) developed a task to disentangle and isolate the two processes using a cueing manipulation within the flicker-paradigm. In the flicker paradigm, target-absent and target-present images, separated by a blank screen, are cycled through, creating the appearance of a flicker with the target appearing and disappearing. Participants searched for a target that was flickering on and off. Although abstract symbols were drawn from the Naval Combat Data System and the Common Warfighting Symbology standard MIL-STD2525B that are used in the Australian and US Navy, participants were untrained in the use of these symbols. Participants viewed displays comprised of symbols drawn from one of four different sets containing seven different symbols. Set 1 (7C/4S) consisted of 7 different colors with 4 different shapes, Set 2 (4C/7S) had 4 colors and 7 shapes, Set 3 (7C/7S) had 7 colors and 7 shapes and Set 4 was in gray scale. In the cued condition, participants received a cue indicating which symbol identity would be the target. This manipulation isolated top-down effects to the cued condition. In the uncued condition, salience alone should guide attention, as participants did not know the target's identity. Target saliency was measured using the Saliency Toolbox (Walther & Koch, 2006). Results showed a significant effect of cueing with faster response times in the cued condition compared to the uncued condition. Unexpectedly, they found a response time benefit for low salience symbols in the cued condition, suggesting that top-down search may inhibit bottom-up control with a stronger inhibition of high salient symbols. Individual symbols differed in a variety of salience characteristics such as the mean salience values and distributions, which may influence a symbol's effectiveness as a cue. However, this experiment did not have enough power to investigate this hypothesis and to analyze the data at the level of the individual symbol. These limitations motivated the current project.

Current Project

The current project seeks to use the knowledge of top-down and bottom-up control to design symbol sets that facilitate particular tasks and performance goals. This knowledge can then be used to help designers develop guidelines for display design.

Chapter 3 introduces Study 1, a pilot study, designed to replicate the effects from Steelman et al. (2013). Study 1 used the same flicker paradigm introduced by Steelman et al. (2013) with the exception of a new symbol set. The new symbol set was designed with the goal to create symbols that differ on a variety of salience characteristics such as the mean salience value and shape of the salience distribution. A cueing manipulation isolated top-down factors to one condition. Response times for every trial were recorded. As found in Steelman et al. (2013), I expected a main effect of cueing, with cueing producing a faster response time compared to uncued trials. I further expected a significant interaction between cueing and color. In the cued condition, low salient symbols should show a response time benefit with response times increasing with target salience, consistent with Steelman et al. (2013). In the uncued condition, faster response times for high salient symbols should be found, indicating guidance by salience. Results confirmed these hypotheses, showing lower response times for cued compared to uncued trials and a response time benefit for low salient symbols in the cued condition. In the uncued condition, the general response time pattern showed a benefit for high salience symbols but did not reach significance. Since results generally corresponded with previous work and expectations, Study 2 investigated whether the benefit for low salient symbols in the cued condition is an artifact of the black background color.

Chapter 4 introduces Study 2, which investigated whether low salient symbols are generally better cues than high salient symbols. Study 2 tested the same hypotheses as Study 1 with the addition of using a background manipulation that preserves the layout of the symbols while manipulating the symbol's contrast to the background color. This background manipulation should vary a symbol's salience but maintain the effects observed in Study 1. On the black background, findings from Steelman et al. (2013) and Study 1 could be replicated, providing more evidence for a benefit for low salient symbols in the cued condition. However, this benefit was not found on the white or the gray background. Instead, results showed a response time benefit for one particular symbol, the blue symbol, in the cued condition across all backgrounds, indicating that other characteristics than salience may determine a symbol's effectiveness as a cue.

Chapter 5 conducted an extended analysis of data from Study 2 to investigate specific symbol characteristics including a variety of salience measures, clutter and distance from the center that may drive the cueing effects observed in the studies. The overall goal was to identify and characterize the factors that make a symbol a good cue. These factors can then be used to help develop design guidelines that support specific tasks and performance goal.

Chapter 3: Study 1

Participants completed a visual search task within the flicker paradigm. Participants viewed images containing 40 symbols drawn from a set of four different symbols. Symbols were unfilled squares in yellow, red, blue or green. These symbols were designed to carefully limit top-down processes. The task was to find the target symbol that was disappearing and reappearing with each flicker of the display. Each trial, participants received either no cue or a cue indicating the identity of the target. The use of stimuli with no meaning coupled with a cueing manipulation allowed us to isolate top-down factors to the cued condition.

Symbols were designed in Matlab and symbol salience was measured using the Saliency Toolbox (Walther & Koch, 2006). Specifically, I chose this model over the others because it contains a graphical user interface making it is easy to use and therefore valuable to practitioners. It has also been successfully used in a variety of studies accurately predicting eye movements, dwell times and response times (Rutishauser, Walther, Koch, & Perona, 2004; Walther, Rutishauser, Koch, & Perona, 2005; Steelman, McCarley, & Wickens, 2013; Steelman et al., 2013).

Study 1 served as a pilot study and sought to replicate the effects found in previous studies (Orchard, 2012; Steelman et al., 2013). My hypotheses are based upon their findings.

"The material contained in this chapter is in preparation for submission to a journal".

H1: Results should show a main effect of cueing, with the cued trials producing a faster response times compared to uncued trials.

H2: There should be a significant interaction between cueing and color. In the uncued condition, salience alone should guide attention, leading to faster response times for high salient symbols.

H2a: In the current study, the average salience values range from .1 (blue symbol) to .7 (yellow symbol). Therefore, based on symbols' average salience, I expect the fastest response times for the yellow symbols and the slowest response times for the blue symbols.

H2b: In the cued condition, low salience symbols will show a response time benefit with faster response times for low salience targets. Therefore, based on the average symbol salience, I expect the fastest response times for the blue targets and the slowest response times for the yellow targets.

Hypotheses are summarized in Table 1.

Table 1

Hypotheses for Study 1

	Effect	Condition	Expected Pattern of Effects
H1	Main effect	Cuing	RT cued < RT uncued
H2	Significant interaction	Cueing + Color	
H2a		Uncued	RTyellow < RTblue
H2b		Cued	RTblue < RTyellow

Methods

Participants. 12 students were recruited through the university research participant pool (6 females and 6 males; M_{age} =20.04, *SD* =1.44). All had normal or corrected-to-normal visual acuity and normal color vision.

Stimuli and Aparatus. Symbols were 30 x 30 pixel squares that subtended 1° x 1° degree of visual angle. The squares were unfilled and their outline had a stroke width of 3 pixels. Symbols were yellow (R=1, G=1, B=0), red (R=1, G=0.5, B=0.5), blue (R=0, G=0, B=0.5) or green (R=0.5, G=0.7, B=0.3). I used the Saliency Toolbox (Walther & Koch, 2006) to select the symbol colors. First, I created multiple variations of a 4-symbol set by changing the RGB values of the symbols on a black background. In order to better quantify the salience characteristics of each symbol, I measured the salience of every symbol in every image and created distributions of these salience values as illustrated in the profiles depicted in Figure 2. These distributions are characterized by the mean, median, standard deviation, skew and excess kurtosis (see Table 2). To normalize the salience values, I calculated the maximum salience ratio by dividing the symbol's maximum salience by the image's maximum salience. This value represents the highest salience value within the 64x64 tile and ensures that the most salient symbol within the image will always have a value of 1. In contrast, a value of 0 means the symbol is not salient and did not even register in the saliency map. I created salience profiles for multiple iterations of multiple symbol sets until I found a set of symbol profiles with a wide range of values, as illustrated in the salience profiles in Figure 2. For example, the yellow symbols' distribution is flatter and wider suggesting salience values of yellow symbols are not consistent across displays and location within each display. In some cases the yellow symbol may be the most salient symbol in the display, in others it may be less salient. The distribution of the blue symbol, however, has a narrower distribution across all displays, meaning that blue symbols consistently have low salience values, and in many cases have a value of zero. To the extent that the observer can use salience to guide search, perhaps a more narrow profile would support better top-down control than a symbol that is inconsistently salient with a wider distribution.

Table 2

Mean, Median, Standard deviation, Kurtosis and Skew of each symbol color based on the Saliency Toolbox (Walther & Koch, 2006).

	Yellow	Red	Green	Blue
Mean	0.729	0.422	0.253	0.106
Median	0.732	0.404	0.219	0.059
StD	0.183	0.172	0.176	0.138
Kurtosis	-0.369	0.598	1.833	5.691
Skew	-.0369	0.684	1.236	2.355

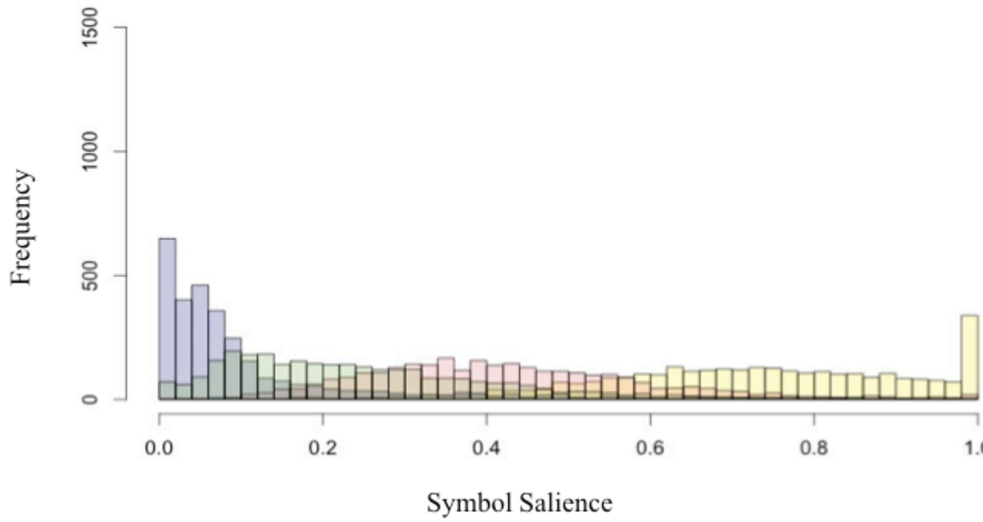

Figure 2. Salience profile as a histogram representing each symbol's salience distribution on a black background.

Displays. Each symbol was placed into a 64x64 pixel tile with one of five alignments for each symbol: upper left (3 pixels horizontally and vertically from the upper left corner), upper right (3 pixels horizontally and vertically from the upper right corner), center, lower left (3 pixels from the lower left corner), lower right (3 pixels from the lower right corner). Tiles were then placed randomly into a 12x12 grid. Each display contained 40 symbols arranged on a black background (Figure 3). The number of yellow, red, blue or green symbols as well as their placement varied randomly between images. Accordingly, each image contained approximately 10 symbols of each color.

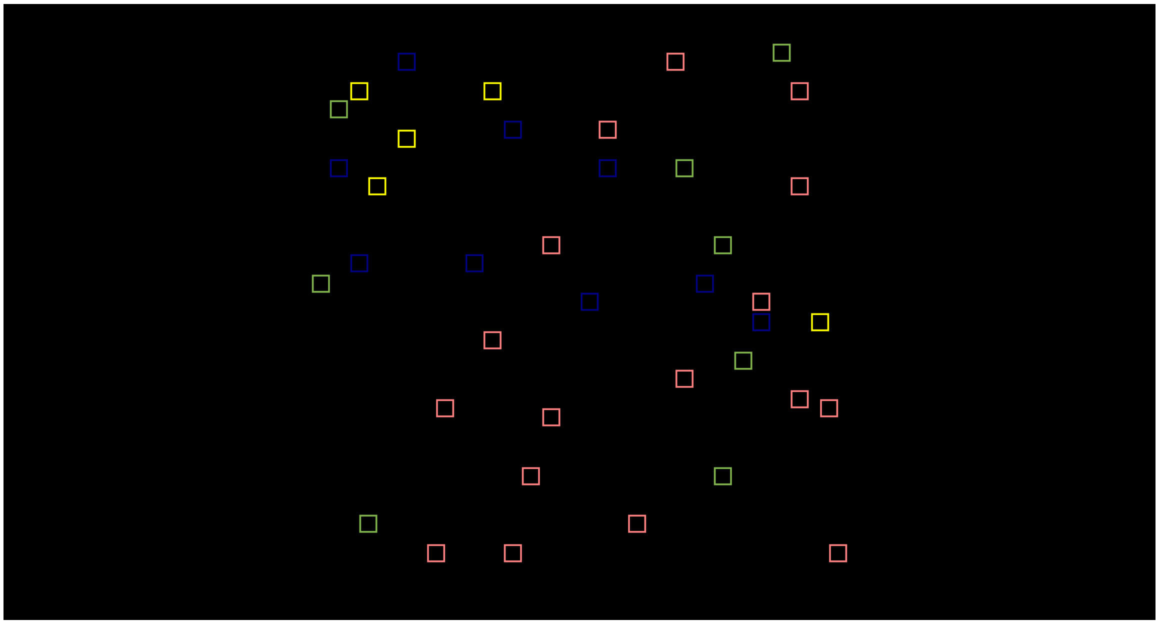

Figure 3. Example image containing 40 symbols.

Three hundred 40-symbol images served as the target-present displays. For each target-present image I created 40 corresponding target-absent image, each having a different symbol eliminated from the display. Each participant viewed the same 300 target-present images. Each participant viewed a different version of the displays. Accordingly, the target ID and location differed for each participant. For each of the 40 sets of stimuli, I calculated the average distance from the target symbol to the center of the display. For each of the 4 colored targets the average distance from the center varied by no more than the width of a single tile.

Stimuli were presented on a 23-inch LCD monitor at a resolution of 1920 x 1080 pixels and a refresh rate of 120 Hz. The corresponding visual angle of the display was 28° x 0.28° at a viewing distance of 57 centimeters.

Procedure and Design. As described earlier, participants performed a change detection task within the flicker paradigm (Rensink, O'Regan, & Clark, 1997), modeled after the task designed by Steelman et al. (2013). The stimuli presentation sequence is displayed in Figure 4. Target-absent stimulus and target-present stimulus were alternately displayed for 240 ms. They were separated by a black screen of 80 ms duration; this gave the illusion of a flickering screen with the target disappearing and reappearing on the screen. There was no time limit to identify the target, but participants were instructed to respond as quickly and accurately as possible. Each trial, participants examined the display and pressed the spacebar when they detected the target. After a response was detected, a confirmation screen appeared with white dots in place of the symbols. Participants indicated the target's location by clicking on the dot that marked the location of the target in the first display. The use of dots on the confirmation screen discouraged any guessing strategies, especially for the cued trials, in which the color of the target was known. On cued trials, participants were presented with an image of the target symbol. The cue effectively reduced the search set to approximately 25% of the total search set. On uncued trials, participants were instructed that the target may be any one of the 4 symbols. The presentation order of cued and uncued trials was randomized.

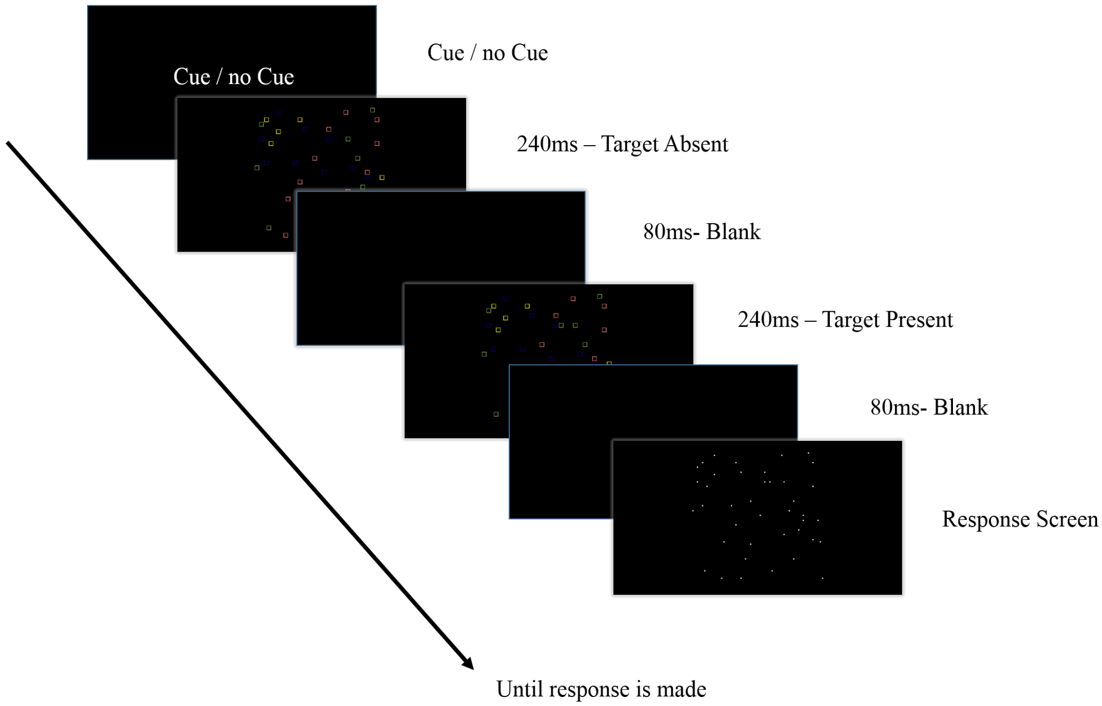

Figure 4. Stimuli presentation sequence. Target absent and target present images cycled through until participants detected the target. A response screen appeared after response detection.

The experiment used a 2 x 4 design with cue (uncued vs cued) and symbol color (yellow, green, red, blue) as within-subject factors. Dependent variables included accuracy and response time (RT) for target detection.

Analysis

Data was analyzed using SPSS's repeated-measures ANOVA and post hoc t-tests. P-values were adjusted using the Bonferroni correction. Greenhouse-Geisser corrections were used when the sphericity assumptions were violated. The first ten trials for each participant served as practice trials and were excluded from the analysis. Trials with incorrect responses (1.89% of all trials) or response times over 30 seconds (0.09% of all trials) were excluded from the analysis. All participants achieved an accuracy level of 94% or higher; two participants obtained a score of 100%.

Results

The analysis showed a main effect of cueing, $F(1, 11) = 113.38$, $p < 0.01$, $MSE = 228195$, $\eta_p^2 = 0.91$. The cued condition elicited a faster response time (M=831.25s, SD=128.56s) than the uncued condition (M=3869.54s, SD=182.82s).

There was also a significant main effect of symbol color, $F(3,33) = 10.57$, $p < 0.01$, $MSE = 136675$, $\eta_p^2 = 0.49$) and a significant interaction between the cueing condition and the symbol colors, $F(3,33) = 9.80$, $p < 0.01$, $MSE = 202797$, $\eta_p^2 = 0.47$. To further examine this interaction, separate repeated-measures ANOVAs were executed. In the uncued condition, there was no significant difference between colors (p =0.2). Figure 5 shows the average response times for each symbol ordered by the most salient symbol on the left to the least salient symbol on the right. The blue symbol shows the fastest response time, which is consistent with the predicted pattern of response times. In contrast to H2b that predicted faster response times for the yellow symbol, the red symbol elicited a faster response than the yellow symbol.

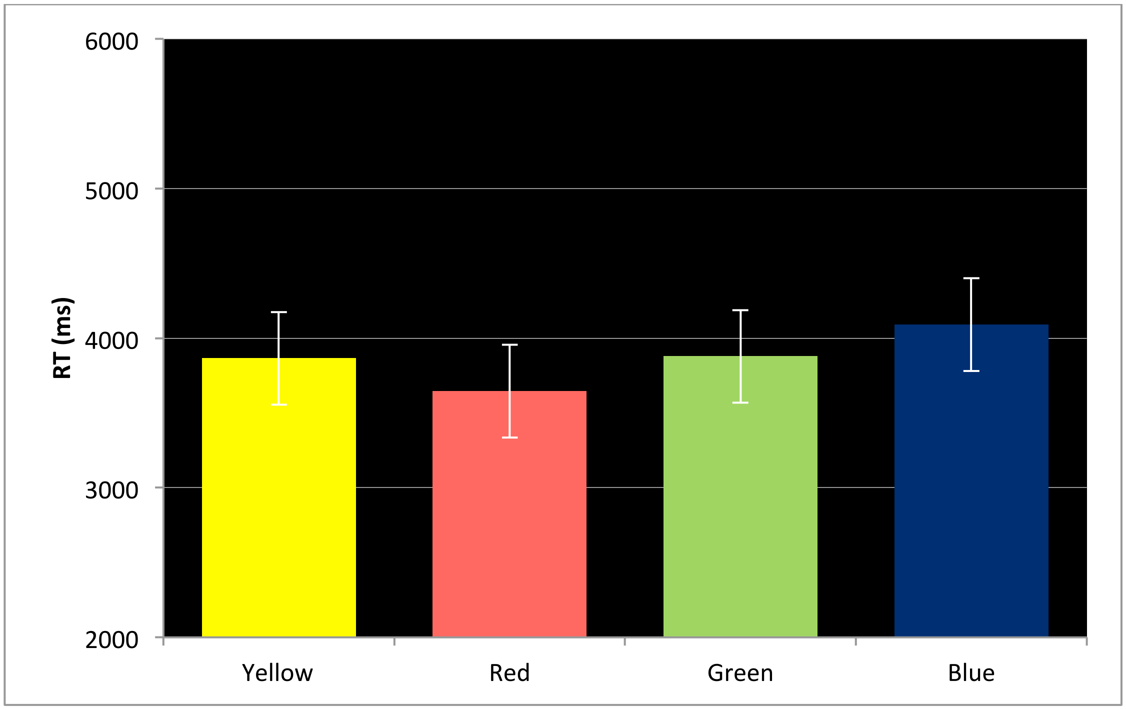

Figure 5. Study 1 mean response times for the uncued condition. Error bars represent within-subject standard errors (Cousineau, 2005).

For the cued condition, in contrast, response times varied among the four symbols, F (3, 33) = 31.38, $p < 0.01$, MSE =96792, $\eta_p^2 = 0.74$. *Post hoc* tests showed that both the blue and red symbol elicited faster response times than both the yellow (both $p < 0.01$) and green symbols (both $p < 0.05$) (see Figure 6). All other pairwise comparisons were non-significant (all p-values>0.09). Cued response times are also listed in Table 3.

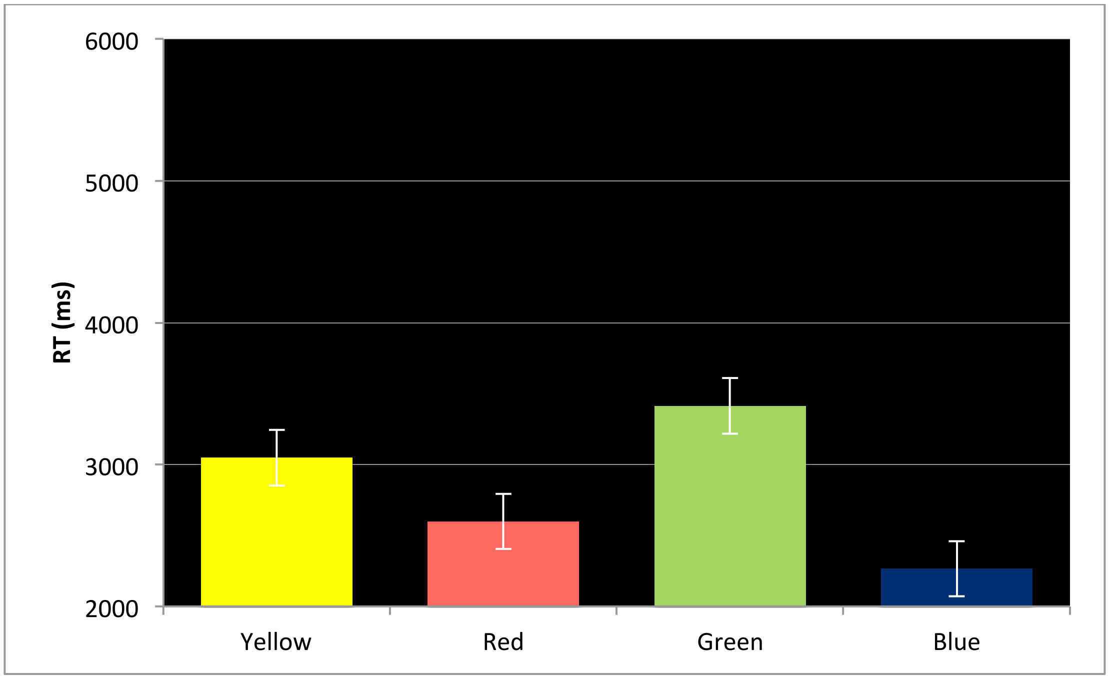

Figure 6. Study 1 mean response times for the cued condition. Error bars represent within-subject standard errors.

Table 3

Mean response times in milliseconds for each target color for the uncued and cued condition.

	Yellow	Red	Green	Blue
Uncued	3865.18 (*SD*=196.39)	3645.11 (*SD*=217.33)	3878.46 (*SD*=197.14)	4089.40 (*SD*=264.06)
Cued	3047.37 (*SD*=141.31)	2598.83 (*SD*=123.78)	3413.20 (*SD*=195.03)	2265.60 (*SD*=130.32)

To further examine the cueing benefit, the cued response times were subtracted from the uncued response times and submitted to a repeated-measures ANOVA. Analysis revealed a main effect of symbol color, F (3, 33) = 9.80, $p < 0.01$, MSE = 405594, $\eta_p^2 = 0.47$. *Post hoc* tests showed a greater response time benefit for the blue symbol compared to the yellow symbol ($p < 0.05$) and the green symbol ($p < 0.01$). In both cases, the blue symbol showed a larger response time benefit. All response time benefits are reported in Table 4.

Table 4

Mean response time benefit in milliseconds for each target.

	Yellow	Red	Green	Blue
Cueing benefit	817.80 (*SD*=177.67)	1046.29 (*SD*=178.22)	465.28 (*SD*=177.72)	1823.80 (*SD*=210.99)

Discussion

The current study investigated the effects of top-down and bottom-up control in a change detection task using four different-colored squares as symbols. A cueing manipulation isolated top-down effects to the cued condition. The uncued condition looked at the guidance by salience alone.

As predicted in Hypothesis 1, there was a significant main effect of cueing with participants producing a faster response time in the cued condition than in the uncued condition. This means, when knowing the target identity, participants were able to find the target faster among its distractors. This is consistent with previous findings indicating the effectiveness of color in cueing (Orchard, 2012) and the successful reduction of the search set (Wolfe et al., 2011).

The data also supports Hypothesis 2, which predicted a significant interaction between cueing and color. However, for the uncued condition, there was no significant difference between symbol colors. Hypotheses 2a predicted a benefit for the yellow symbol compared to the blue symbol. Although a significant effect of color did not obtain, the general pattern of response times is consistent with Hypothesis 2a, with the blue symbol eliciting a slower response time compared to the yellow symbol.

Notably, in the cued condition, the blue symbol – the least salient symbol within the set – produced the greatest response time benefit, consistent with Hypotheses 2b that predicted the fastest response times for the blue symbol. These results are consistent with those of Steelman et al. (2013) and Orchard (2012) who found a response time benefit for low salience symbols in the cued condition. Hypotheses 2b also suggested the slowest response times for the yellow symbol. The data, however, showed that not only the yellow but also the green symbol elicited significantly slower response times than the blue symbol.

Study 1 successfully replicated effects from Steelman et al. (2013) indicating the existence of a response time benefit for low salience symbols. However, Steelman et al. (2013) and Study 1 both displayed symbols on a black background. To investigate whether the findings are an artifact of the symbol/black background combination, Study 2 will add a background manipulation to the existing paradigm.

Study 2 will be an expanded replication of Study 1. In addition to the black background, the same experiment will be conducted using a white and a gray background. The background manipulation maintains the position and color of every symbol on the display. However, since changing the background color effects the symbol-background contrast, symbols that are highly salient on one background color may not be salient on another. This will also lead to different salience profiles of each symbol.

As in Study 1, results should show a main effect of cueing, with cueing producing faster response times compared to uncued trials across all background conditions (Hypothesis 1). There should also be a significant three-way interaction between cueing, color and backgrounds (Hypothesis 2) and a significant interaction between cueing and color (Hypothesis 3). As different symbol colors will be the most and the least salient in each of the three background conditions, *post-hoc* paired t-tests should reveal that different colored symbols are fastest and slowest in each background condition. Across all backgrounds, high salience targets should therefore produce the fastest response times in the uncued condition and the slowest response times in the cued condition.

Chapter 4: Study 2

In Study 2, two more background colors (gray and white) were tested in addition to the black background from Study 1 (see Figure 7). This background manipulation changed each symbol's salience profile, while preserving the symbols' color and their location and arrangement within the display. As illustrated in Figures 8, 9 and 10 and Table 5, the salience profiles and salience characteristics have changed. For example, the yellow symbol was the highest salience symbol and the blue was the least salience symbol on the black background. On the white background, however, the yellow symbol is now the least salience symbol and the blue symbol is the highest.

Figure 7. Example display containing 40 symbols on the black, white and gray background.

"The material contained in this chapter is in preparation for submission to a journal".

Table 5

Mean, Median, Standard deviation, Kurtosis and Skew of each symbol color depended on background color based on the Saliency Toolbox (Walther & Koch, 2006).

BG		Yellow	Red	Green	Blue
	Mean	0.729	0.422	0.253	0.106
	Median	0.732	0.404	0.219	0.059
Black	StD	0.183	0.172	0.176	0.138
	Kurtosis	-0.369	0.598	1.833	5.691
	Skew	-.0369	0.684	1.236	2.355
	Mean	0.181	0.308	0.185	0.816
	Median	0.165	0.298	0.170	0.839
White	StD	0.099	0.112	0.113	0.142
	Kurtosis	4.517	2.816	2.598	0.114
	Skew	1.781	0.975	1.238	-0.746
	Mean	0.660	0.268	0.081	0.787
	Median	0.664	0.258	0.026	0.801
Gray	StD	0.149	0.113	0.124	0.149
	Kurtosis	-0.132	1.953	4.204	-0.128
	Skew	-0.133	0.924	2.089	-0.553

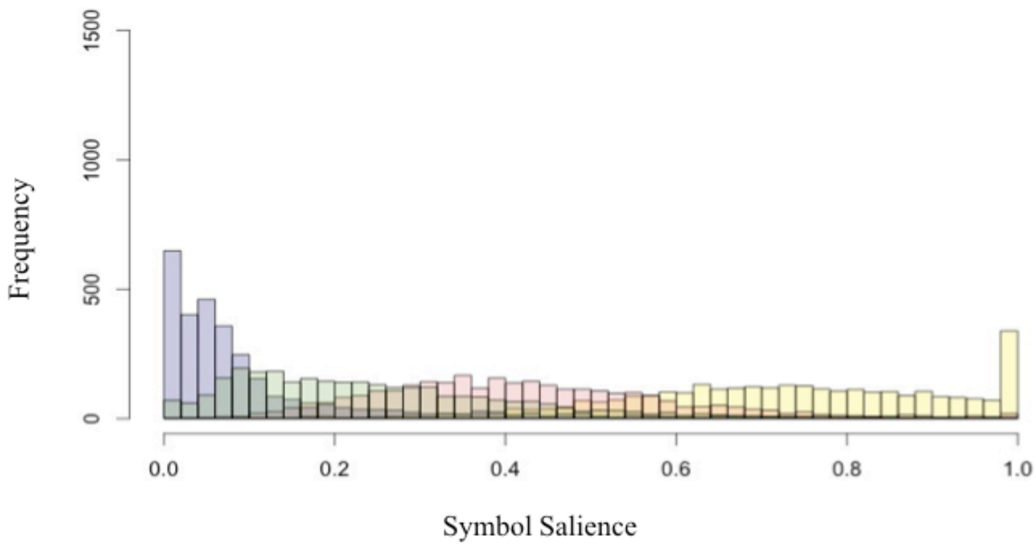

Figure 8. Salience Profile as histograms of each symbol on the black background.

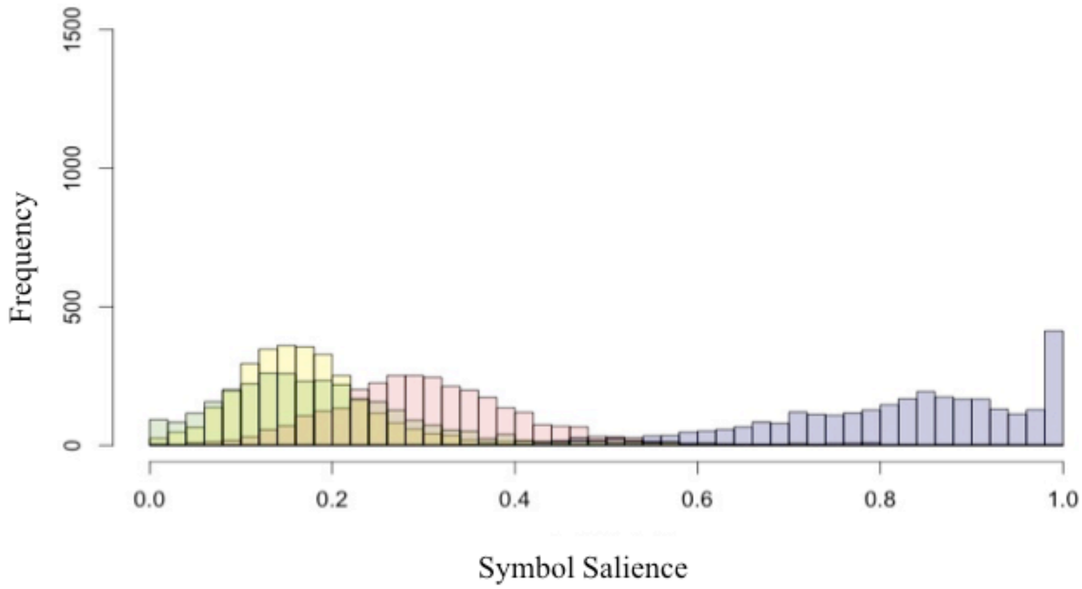

Figure 9. Salience Profile as histograms of each symbol on the white background.

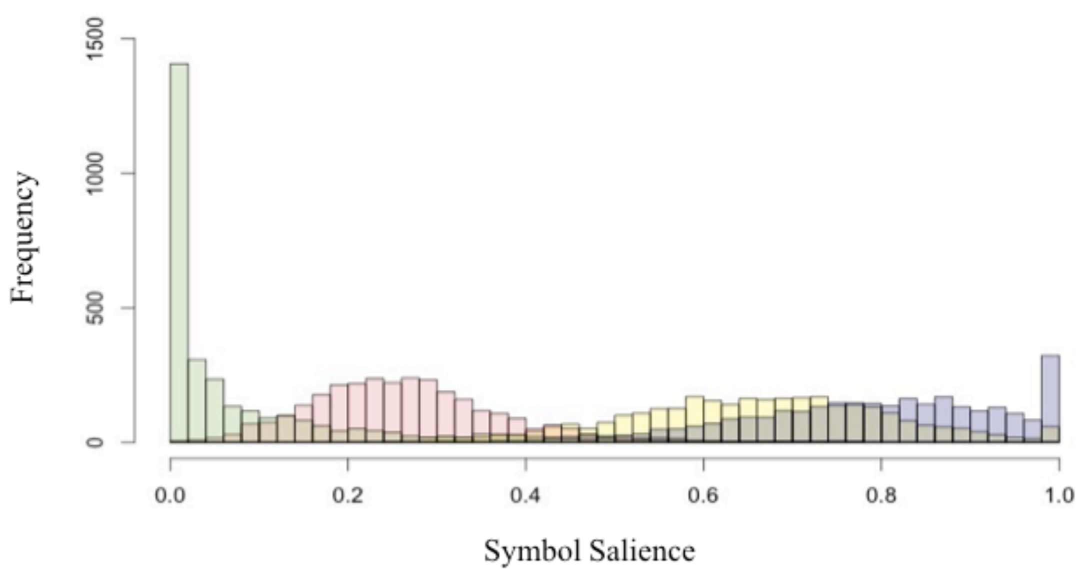

Figure 10. Salience Profile as histograms of each symbol on the gray background.

Study 2 served as an extended replication of Study 1 with the addition of a background manipulation. My hypotheses are based on previous findings (Steelman et al., 2013; Study 1) with the exception that findings are dependent on the background condition.

H1: Analysis should show a main effect of cueing, with cueing producing a faster response time compared to uncued trials for all background colors

H2: There should be a significant three-way interaction between cueing, color and backgrounds.

H3: There should also be a significant interaction between cueing and color. However this interaction should be mediated by background color.

H3a: For the black background, in the cued condition, the blue symbol should elicit the fastest repose times and the yellow symbol the slowest.

H3b: For the white background, in the cued condition, the yellow symbol should elicit the fastest response times and the blue symbol the slowest.

H3c: For the gray background, in the cued condition, the green symbol should elicit the fastest response times and the blue symbol the slowest.

H3d: For the black background, in the uncued condition the yellow symbol should elicit the fastest response times and the blue symbol the slowest.

H3e: For the white background, in the uncued condition, the blue should elicit the fastest response times and the yellow symbol the slowest.

H3f: For the gray background, in the uncued condition, the blue symbol should elicit the fastest response times and the green symbol the slowest.

Hypotheses are summarized in Table 6.

Table 6

Hypotheses Study 2

	BG	Effect	Condition	Expected Pattern of Effect
H1		Main Effect	Cueing	
H2		Three-Way-Interaction	Cueing+Color+BG	
H3		Sig. Interaction mediated by BG	Color+Cueing	
H3a	Black		Cued	RTblue < RTyellow
H3b	White		Cued	RTyellow < RTblue
H3c	Gray		Cued	RTgreen < RTblue
H3d	Black		Uncued	RTyellow < RTblue
H3e	White		Uncued	RTblue < RTyellow
H3f	Gray		Uncued	RTblue < RTgreen

Methods

The methods were generally consistent with Study 1, with the exception that three different background colors were used. This resulted in a 3 (background: black, gray or white) x 2 (cue condition: uncued, cued) x 4 (color: yellow, red, green, blue) mixed factorial design. Cueing and symbol color were manipulated within subjects. The background condition was manipulated between subjects.

Participants. 94 students participated for course credit through the university research participant pool (29 females and 65 males; M_{age} = 19.87, *SD* =1.42). All had normal or corrected-to-normal visual acuity and normal color vision. There were 33 participants in the black background condition, 31 in the gray background and 30 in the white background condition.

Analysis

Data was analyzed using SPSS's repeated-measures ANOVA and *post hoc* t-tests. P-values were adjusted using the Bonferroni correction. Greenhouse-Geisser corrections were used when the sphericity assumptions were violated. The first ten trials for each participant served as practice trials and were excluded from the analysis. 51 trials with slow reaction times (>30s) were also excluded, representing 0.18% of all trials. All participants reached an accuracy level of 94% or higher, with 30 participants obtaining a score of 100%.

Results

The analysis showed a significant effect for cueing, F (1, 91) =689.55, $p < 0.01$, MSE =867395, $\eta_p^2 = 0.88$, symbol colors, F (3, 89) = 49.54, $p < 0.01$, MSE =258498, $\eta_p^2 = 0.37$, and background colors, F (2, 91) =9.03, $p < 0.01$, MSE =5060518, $\eta_p^2 = 0.17$. There were three significant two-way interactions. First between the cueing condition and the symbol colors, F (3, 273) = 37.41, $p < 0.01$, MSE =241833, $\eta_p^2 = 0.29$: second, between the cueing condition and background colors, F (2,91)= 18.92, $p < 0.01$, MSE =16410312, $\eta_p^2 = 0.29$; and lastly, the interaction between the symbol colors and the background color, F (6, 273)= 7.39, $p < 0.01$, MSE =1909708, $\eta_p^2 = 0.14$. The three-way interaction between cueing condition, symbol colors, and background colors also reached significance, F (6, 273)= 4.86, $p < 0.01$, MSE =1174119, $\eta_p^2 = 0.10$. To further examine these interactions, separate repeated-measures ANOVAs examined the effects of cueing and symbol color for each background.

Black Background. For the black background the analysis showed a main effect for cueing, F (1, 32) = 306.87, $p < 0.01$, MSE =329690, $\eta_p^2 = 0.91$, and for symbol colors, F (3, 96) = 19.82, $p < 0.01$, MSE =190386, $\eta_p^2 = 0.38$.

Notably, there was a significant interaction between the cueing condition and the symbol colors, F (3,96)= 42.31, $p < 0.01$, MSE =137667, $\eta_p^2 = 0.57$. To further examine this interaction, two separate repeated-measures ANOVAs for the uncued and for the cued condition were executed.

For the uncued condition, response times varied among the four symbols F (3, 96) = 10.07, $p < 0.01$, MSE =212354, $\eta_p^2 = 0.24$. *Post hoc* tests revealed faster response times for the yellow and the red symbol compared to the blue symbol ($p < 0.01$). All other pairwise comparisons were nonsignificant (all p-values>0.051). Figure 11 shows mean response times for every symbol.

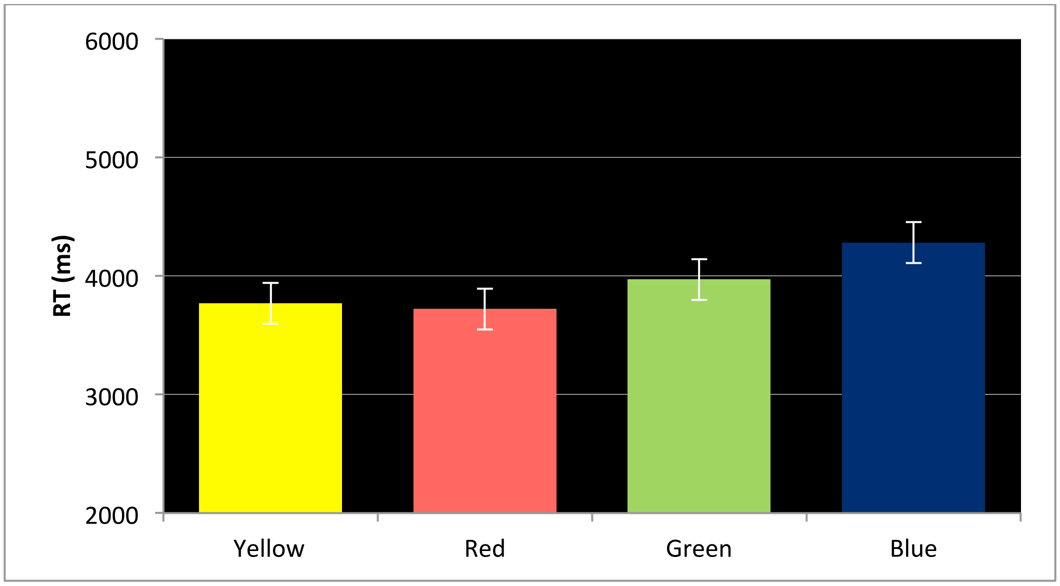

Figure 11. Study 2 mean response times for the uncued condition for the black background. Error bars represent within-subject standard errors.

For the cued condition, there was a main effect of symbol color, F (2.01, 64.21) =64.47, $p < 0.01$, MSE =172993, $\eta_p^2 = 0.67$. *Post hoc* tests showed that both the blue and the red symbol elicited a faster response time than the yellow and the green symbol ($p < 0.01$). All other pairwise comparisons were nonsignificant (all p-values>0.08). The response times are displayed in Table 7 and depicted in Figure 12.

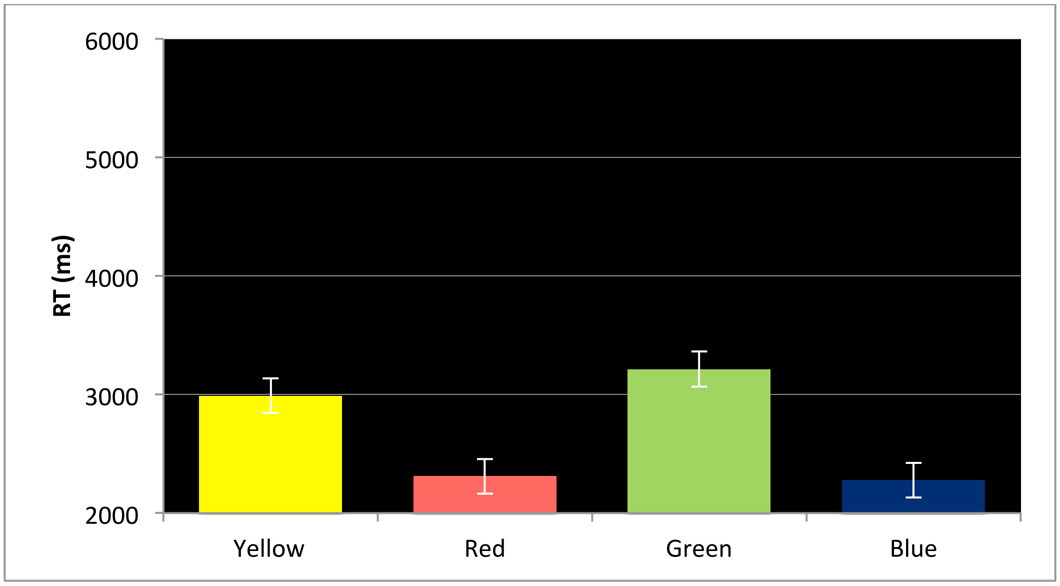

Figure 12. Study 2 mean response times for the cued condition for the black background. Error bars represent within-subject standard errors.

Table 7

Mean response times in milliseconds for every symbol color for the uncued and cued condition for the black background.

	Yellow	Red	Green	Blue
Uncued	3770.14 (*SD*=126.73)	3722.171 (*SD*=120.212)	3971.17 (*SD*=111.44)	4282.37 (*SD*=144.17)
Cued	2990.39 (*SD*=85.54)	2311.39 (*SD*=63.31)	3214.09 (*SD*=104.45)	2277.55 (*SD*=66.19)

To examine the cueing benefit a repeated measures ANOVA was executed. Results showed a main effect of symbol color, F (3, 96) = 42.31, p < 0.01, MSE = 275335, η_p^2 = 0.57. *Post hoc* tests showed a greater response time benefit for the blue symbol compared to any other symbol color ($p < 0.01$). The red symbol showed a greater benefit compared to the yellow and green symbol ($p < 0.01$). All cueing benefits are displayed in Table 8.

Table 8

Mean response time benefit in milliseconds for each target color.

	Yellow	Red	Green	Blue
Cueing benefit	779.75 (*SD*= 99.67)	1410.78 (*SD*=90.65)	757.08 (*SD*=77.59)	2004.82 (*SD*=144.36)

White Background. For the white background the analysis showed main effects for cueing, $F\ (1, 29) = 213.89$, $p < 0.01$, MSE =993883, $\eta_p^2 = 0.88$, and symbol color, $F\ (3, 87) = 19.29$, $p < 0.01$, MSE =327590, $\eta_p^2 = 0.40$.

There was a significant interaction between the cueing condition and the symbol colors, $F\ (3, 87)= 10.55$, $p < 0.01$, MSE =271388, $\eta_p^2 = 0.27$. To further examine this interaction, two separate repeated-measures ANOVAs for the uncued and for the cued condition were executed.

For the uncued condition, there was no significant difference in response time among colors, $F\ (3, 87) = 2.43$, $p > 0.05$, MSE =474555, $\eta_p^2 = 0.08$ (see Figure 13).

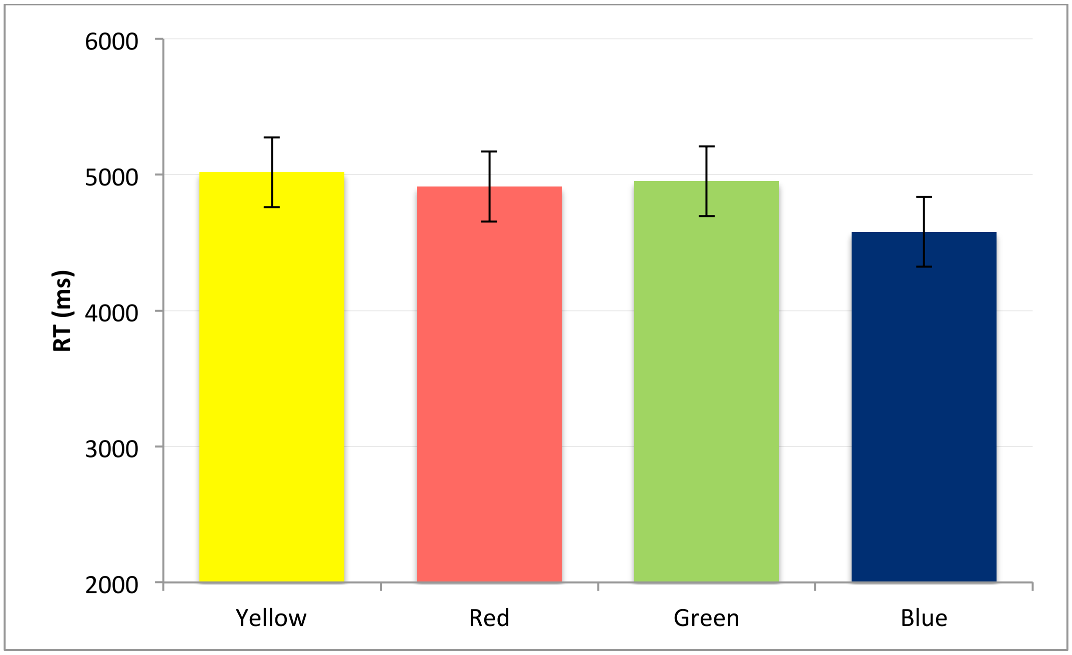

Figure 13. Study 2 mean response times for the uncued condition for the white background. Error bars represent within-subject standard errors.

For the cued condition, the ANOVA resulted in main effect of symbol color, F (3,87) = 64.52, $p < 0.01$, MSE =124424, $\eta_p^2 = 0.69$ (see Figure 14). *Post hoc* tests showed that the blue and the red symbol elicited a faster response time than the yellow and the green symbol (p<0.01). The yellow symbol elicited a faster response time than the green symbol (p<0.01). Other pairwise comparisons were non-significant (all p-values>0.27). All response times are reported in Table 9.

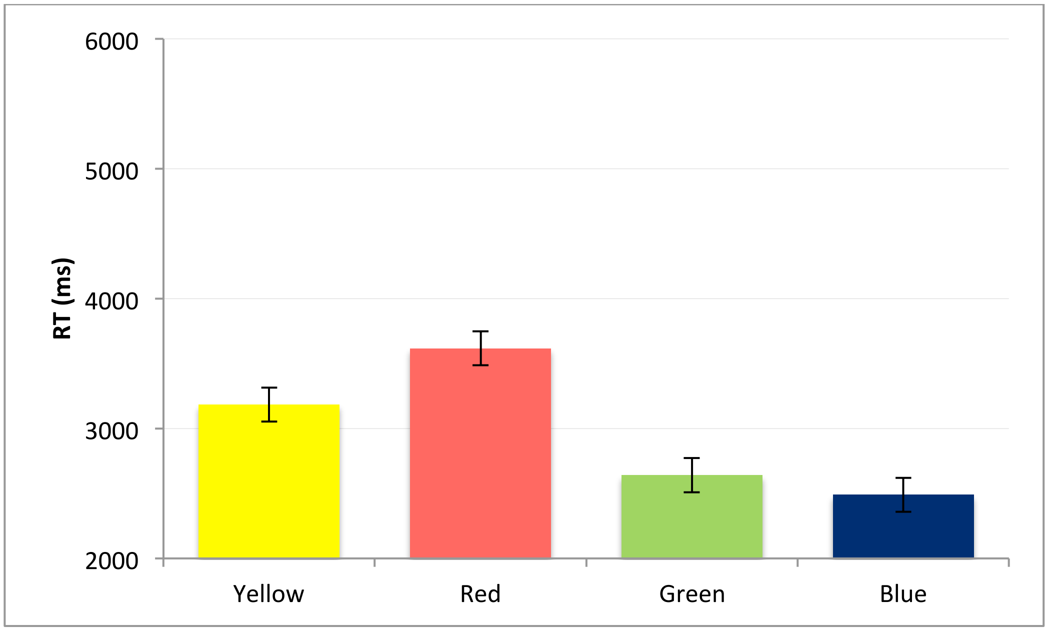

Figure 14. Study 2 mean response times for the cued condition for the white background. Error bars represent within-subject standard errors.

Table 9

Mean response times in milliseconds for every symbol color for the uncued and cued condition for the white background.

	Yellow	Red	Green	Blue
Uncued	5018.15 (*SD*= 260.41)	4952.09 (*SD*= 223.40)	4912.82 (*SD*= 223.08	4578.78 (*SD*= 187.01)
Cued	3184.85 (*SD*= 159.96)	2640.69 (*SD*=106.72)	3616.88 (*SD*=154.16)	2489.96 (*SD*= 116.61)

A repeated-measures ANOVA examined cueing benefits. Results showed a significant difference between symbol colors, F (3, 87) = 10.55, $p < 0.01$, MSE = 54277, $\eta_p^2 = 0.27$. *Post hoc* tests showed a greater response time benefit for the blue symbol compared to the green symbol ($p < 0.01$). The red symbol showed a greater benefit compared to the yellow symbol ($p < 0.05$); and the green symbol ($p < 0.01$). All response time benefits are displayed in Table 10.

Table 10

Mean response time benefit for each target color.

	Yellow	Red	Green	Blue
Cueing benefit	1833.30 (*SD*=195.92)	2311.40 (*SD*=148.70)	1295.94 (*SD*=189.05)	2088.52 (*SD*=155.89)

Gray Background. For the gray background the analysis showed significant main effects for cueing, F (1, 30) = 234.81, $p < 0.01$, MSE =1318674, $\eta_p^2 = 0.89$, and symbol colors, F (3, 90) = 26.99, $p < 0.01$, MSE =264361, $\eta_p^2 = 0.47$.

There was a also significant interaction between cueing and symbol color, F (3, 90)= 8.85, $p < 0.01$, MSE =324372, $\eta_p^2 = 0.23$. To further examine this interaction, separate repeated measures ANOVAs were executed for the uncued and for the cued condition.

For the uncued condition, there was a main effect of symbol color, F (3,90) = 7.05, $p < 0.01$, MSE=443850, $\eta_p^2 = 0.19$. *Post hoc* tests revealed faster response times for the yellow symbol compared to both the red and green symbol ($p < 0.01$). The blue symbol showed a faster response time than the green symbol ($p < 0.05$). All other pairwise comparisons were nonsignificant (all p-values>0.052). Mean response times for every symbol are depicted in Figure 15.

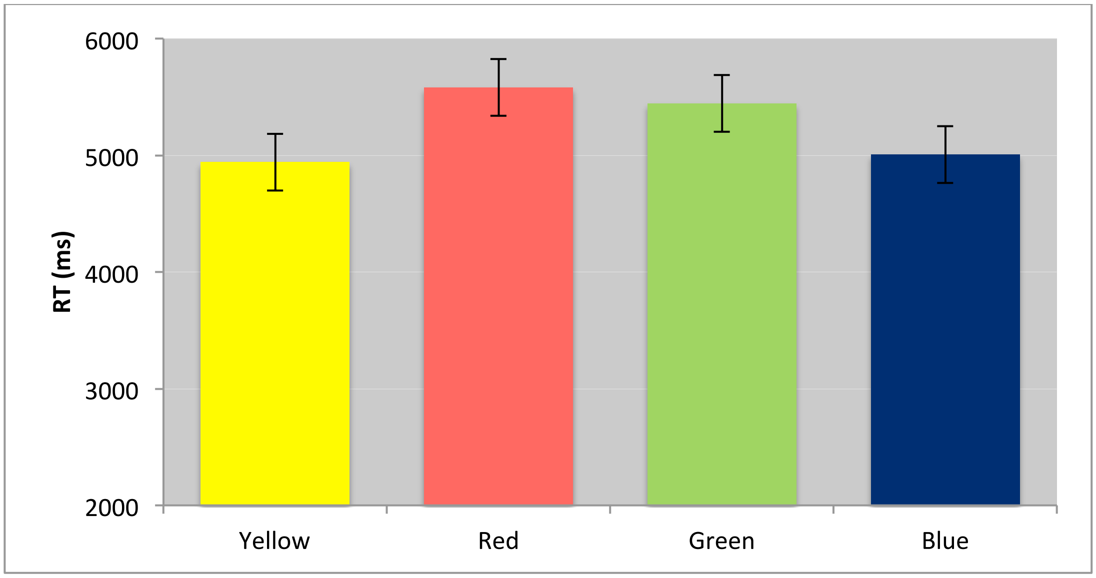

Figure 15. Study 2 mean response times for the uncued condition for the gray background. Error bars represent within-subject standard errors.

For the cued condition, the ANOVA showed a main effect of symbol color, F (3,90) =47.46, $p < 0.01$, MSE =144883, $\eta_p^2 = 0.61$. *Post hoc* tests showed that the blue symbol elicited a faster response time than all the other colors ($p < 0.01$). The red symbol produced a faster response time than the yellow and the green symbol ($p < 0.01$). All other pairwise comparisons were non-significant (all p-values > 0.23). All response times are displayed in Table 11 and depicted in Figure 16.

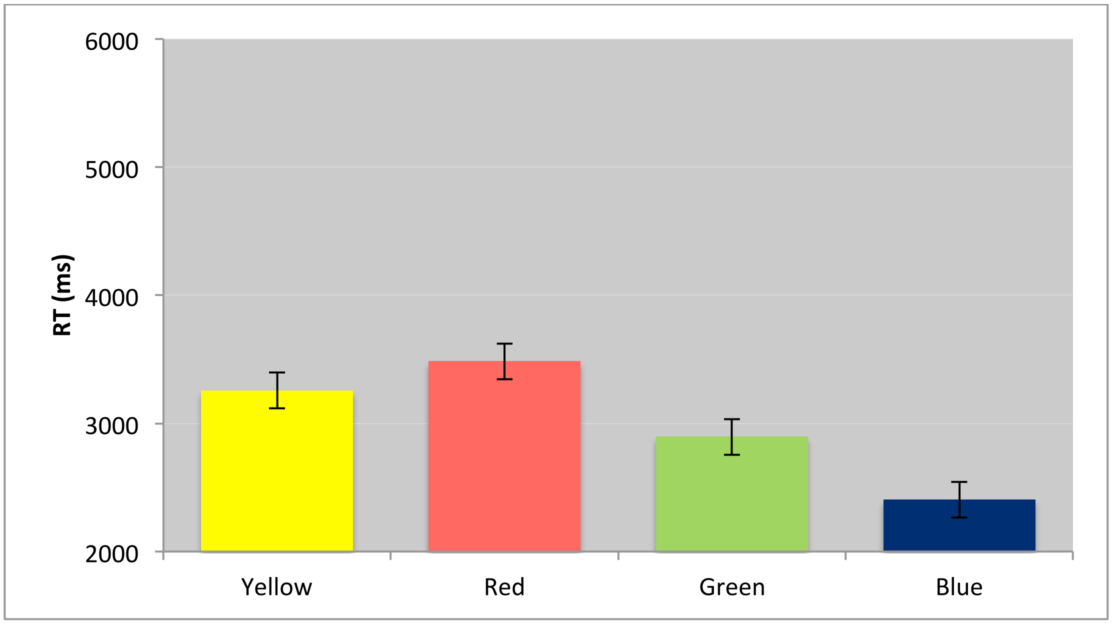

Figure 16. Study 2 mean response times for the cued condition for the gray background. Error bars represent within-subject standard errors.

Table 11

Mean response time in milliseconds for every symbol color for the uncued and cued condition.

	Yellow	Red	Green	Blue
Uncued	4942.58 (*SD*=231.90)	5446.27 (*SD*= 274.06)	5583.32 (*SD*= 262.18)	5007.49 (*SD*= 268.19)
Cued	3256.66 (*SD*=182.95)	2894.63 (*SD*= 160.07)	3484.40 (*SD*=159.51)	2404.85 (*SD*= 106.42)

To examine the cueing benefits, a repeated measure ANOVA for the gray background was executed. Results showed main effect for symbol color, F (3, 90) = 8.85, $p < 0.01$, *MSE* = 648744, $\eta_p^2 = 0.23$. *Post hoc* tests showed a greater response time benefit for both the blue symbol ($p < 0.01$) and the red symbol ($p < 0.01$) compared to the yellow symbol. All response time benefits are displayed in Table 12.

Table 12

Mean Response time benefit in milliseconds for each target color.

	Yellow Target	Red Target	Green Target	Blue Target
Cueing benefit	1685.92 (*SD*= 176.86)	2551.64 (*SD*=194.33)	2098.92 (*SD*= 188.08)	2602.63 (*SD*= 208.42)

Discussion

Study 2 served as an expanded replication of Study 1 to determine if the cueing effects were truly driven by salience and were not an artifact of the particular set of symbol colors selected in Study 1. Study 2 used a background color manipulation to effect symbol salience. As salience is dependent on a target's contrast relative to its surroundings (Wolfe & Horrowitz, 2004), manipulating the background color should affect the symbol salience, while maintaining the symbol's color and arrangement on the display. As in Study 1, a cueing manipulation isolated top-down effects in the cued condition, whereas the uncued condition served to investigate salience-driven effects only.

As predicted in Hypotheses 1, participants produced a faster response time in the cued condition than in the uncued condition for every background color. These findings are consistent with Study 1 and previous studies (Orchard, 2012; Steelman et al., 2013) indicating top-down feature guidance based on color. When the viewers knew the target color, they were able to find the target more quickly.

Analysis also found support for Hypotheses 2 that predicted a significant three-way interaction between cueing, symbol color, and background color. After further investigating the interaction between symbol color and cueing individually for each background, a different pattern of effects for each background color was revealed. Although, Hypothesis 3 predicted different pattern of effects for each background color, the specific patterns observed were inconsistent with Hypotheses 3a, 3b, 3c, 3d and 3f. A comparison between expected and observed response times across studies and backgrounds is displayed in Figure 17.

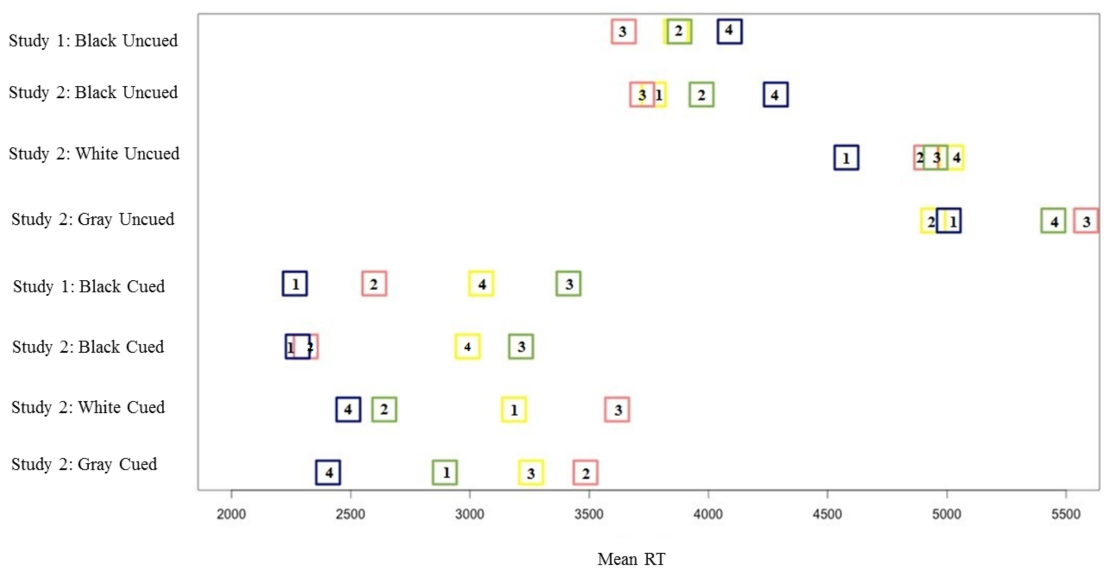

Figure 17. Summary of observed and expected response times across all backgrounds and studies. Numbers indicate the predicted response time pattern (ranked from fastest (1) to slowest (4)) based on a symbol's average salience values.

For the uncued conditions, Hypotheses 3d, 3e and 3f predicted that high salience symbols should elicit faster response times than low salience symbols. However, since salience is dependent on the background, the color of the highest salience symbol should vary by background color. For the black background, the salience of each symbol (ranked from high to low) was yellow, green, red and blue. The yellow symbol elicited a faster response time than the blue symbol, which is consistent with the predicted ordering as illustrated in Figure 17. The red symbol, however, elicited faster response times than the yellow symbol, which is not perfectly consistent with the predicted ordering. Nevertheless, the results generally support Hypothesis 3d and are consistent with the general pattern of results from Study 1 and previous studies (Orchard, 2012; Steelman et al., 2013).

For the white background, the predicted ordering based on the salience of each symbol (ranked from high to low) was blue, red, green and yellow. However, observed effects showed no difference between symbol colors. The general pattern of response times, however, follows the predicted pattern of effects with the lowest response times for the blue symbol and the highest response times for the yellow symbol, which aligns with Hypothesis 3e (see Figure 17).

For the gray background, the predicted ordering based on salience of each symbol (ranked from high to low) was blue, yellow, red and green. As predicted the blue symbol elicited faster response times than the green symbol, consistent with Hypothesis 3e. However, the yellow elicited even faster response times than the blue symbol and the red symbol produced lower response times than the green symbol, inconsistent with the predicted ordering.

In summary, the results from each background condition support the hypothesis that high salience symbols elicit faster response times than low salience symbols in the uncued condition in which search was driven exclusively by bottom-up factors. Although salience did not perfectly predict the ordering of response times, in 1 out of 4 studies/conditions the most salient target tended to produce the fastest response times and in 2 out of 4 studies/conditions the least salient target produced the slowest response times.

In the cued condition, across all background conditions, Hypotheses 3a, 3b and 3c predicted that the low salience symbols would elicit faster response times than high salience symbols. For the black background, the salience of each symbol (ranked from low to high) was blue, red, green and yellow. The blue symbol elicited faster cued response times than the yellow symbol, supporting Hypothesis 3a and consistent with findings from Study 1. Inconsistent with the predicted ordering, however, the green symbol elicited the slowest response times instead of the yellow symbol (see Figure 17).

For the white background, the salience of each symbol (ranked from low to high) was yellow, red, green and blue. However, I observed a different outcome that did not support this ordering and Hypothesis 3b. According to Hypothesis 3b, the yellow symbol should have produced a faster response time than the blue symbol. Surprisingly, the blue symbol once again elicited faster response times than the yellow symbol. The red symbol instead of the blue symbol elicited the slowest response times. Overall, the predicted ordering was completely different than the predicted ordering.

For the gray background, the salience of each symbol (ranked from low to high) was green, red, yellow and blue. Hypothesis 3c predicted the green symbol to show faster response times than the blue symbol. However, the blue symbol again produced faster response times than the green symbol, reversing the predicted ordering based on salience. The red symbol again showed the slowest response times, which is inconsistent with the predicted ordering that expected the red symbol to produce the second fastest results. In summary, across all backgrounds the blue symbol, the highest salience symbol on the white and the gray background and the lowest salience symbol on the black background, elicited the fastest cued response times.

In contrast to previous studies (Steelman et al., 2013) and Study 1, response time data from the white and the gray background do not support the hypothesis that low salience targets are the best cues for cued trials. This inconsistency suggests that it is not the salience value that drives cued response times. What qualities does the blue symbol have that makes it such an effective cue across backgrounds? Below, I consider several possible explanations for this finding.

It is possible that cueing benefits are not driven by the average salience values of the symbols as tested in Study 1 and 2, but other characteristics of a symbol's salience profile (see Figure 18). To the extent that salience itself can be used as a cue, the width (standard deviation) of the salience distribution may provide an indicator of whether or not a target is a good cue. For example as illustrated in Figure 18, the blue symbol has a narrower distribution, which may make it a better cue than a symbol with a wider distribution because, regardless of the layout of the particular display, the blue symbol consistently has a high salience value (white and gray backgrounds) or a low salience value (black background). This consistency may allow the viewer to more easily adopt an attentional set for that class of symbols and effectively ignore the other symbols. The yellow symbol, in contrast, has a wider distribution as shown in Figure 18, indicating that the yellow symbol varies in salience across displays. This variability in salience may suggest that an individual symbol's salience value may be more strongly affected by the arrangement of symbols within the display and surrounding clutter than a symbol with a more narrow salience distribution. Accordingly, this may make it more difficult for the viewer to easily reduce his or her search set.

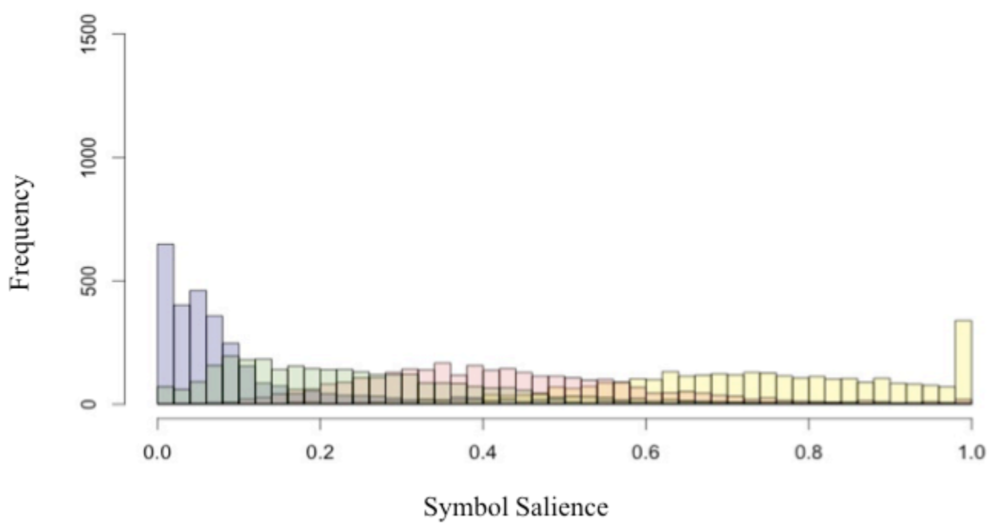

Figure 18. Salience Profile as histograms of each symbol on the black background.

Besides salience, another factor that could potentially influence the size of the cueing benefit is a symbol's discriminability from other symbols. If a symbol is difficult to discriminate from another symbol within the same set, then the symbol will be less effective as a cue because the viewers cannot reduce their search set to a single color. In the current symbol set, perhaps the green and the yellow symbol were too similar to one another. If this was the case, the viewers would not be able to reduce their search set, which would lead to increased response times for the two symbols. In the black background condition, both the yellow and the green show a similar cueing benefit, which was over 1000 ms smaller than the cueing benefit of the red and the blue symbol, consistent with this explanation. For the white and the gray background conditions, the cueing benefit for green and for yellow are still smaller than for the red and the blue symbol. However, the cueing benefits for the green and the yellow symbol are also highly different, indicating that it is not simply a discriminability issue.

To investigate this issue further requires a measure of symbol-symbol discriminability. Although salience may be, to some degree, driven by symbol-symbol discriminability, they are not the same concept. Salience should be influenced by both symbol-background contrast and symbol-symbol discriminability. Study 2 manipulated symbol-background contrast, but the symbol-symbol discriminability remained the same across all background colors. A preliminary study (Steelman & North, 2016) employed the perceptual Euclidian distance (PED) as a measure of symbol-symbol discriminability (Gijsenij, Gevers, & Lucassen, 2009). Results showed a strong negative correlation between the average PED_{Avg} among symbol colors and the cued response times. These findings suggest that PED_{Avg} may be a useful measure of target-distractor similarity and may serve as a strong predictor of response times in cued search tasks.

Although the average salience values did not drive response times strongly in the cued condition from Study 2, it may be possible that our measure of salience was not sensitive enough to detect salience differences between symbols in our symbol set. In both Study 1 and 2 the maximum salience ratio was used instead of the maximum salience values to normalize the salience values. The maximum salience ratio was calculated by dividing the symbol's maximum salience by the image's maximum salience. Accordingly, the most salient symbol in the display always had a salience value of 1. Although, Steelman et al. (2013) used this calculation of salience in the previous work, this may not be the best approach as it may limit the ability to account for response times across background colors. Maximum salience values may be more useful in investigating differences between trials and background conditions. Therefore, future analyses should include the maximum salience values instead of the maximum salience ratio.

Another concern is whether the Saliency Toolbox (Walther & Koch, 2006) provided a valid measure of symbol salience. Although the Saliency Toolbox provides a usable GUI and has been used in a variety of studies, other salience models may be more sensitive to salience differences between symbols in our symbol set. I passed the stimulus images through each of the four models summarized in the literature review, and they produced different rank orderings of the symbols' salience values. Table 13 provides an overview of the models and their accuracy in predicting the observed response times in the uncued condition. Accuracy, in this case, is defined as the correct ordering of response times based on a symbol's average salience value as measured by the model. The Saliency Toolbox only predicted the exact observed response times ordering (blue, red, green, yellow; ranked high to low salience) on the white background. For the black background, the simpsal model (Model 3) accurately predicted the observed response times (red, yellow, green, blue) according to the mean salience values of each symbol. These results suggest that none of the models accurately predict the ordering of response times based on average salience values for all backgrounds.

Table 13

Accuracy of the 4 models in predicting observed response times based on the symbols average salience value. Each row lists the order of the symbols from slowest to fastest response times. A checkmark (✓*) indicates that the model accurately predicted the ordering of response times for a given background.*

	Model 1: Sal. Toolbox	Model 2: GBVS	Model 3: Simpsal	Model 4: SigSal
Uncued Black (BGYR)	X	X	✓	X
Uncued White (YGRB)	✓	X	X	X
Uncued Gray (RGBY)	X	X	X	X

However, these results are based on the maximum salience ratio instead of the maximum salience values. Each model produces different salience profiles and salience values, indicating that the models may not be sensitive to salience differences between symbols, but rather are sensitive to different aspects. Table 14 shows the four models salience profile characteristics. Future work should therefore investigate the other salience models in more detail including the use of the maximum salience values.

Table 14

Mean salience of each symbol color depended on background color based on the four salience models.

BG	Symbol	Model 1: Sal. Toolbox	Model 2: GBVS	Model 3: Simpsal	Model 4: SigSal
	Yellow	0.7285	0.5532	0.5857	0.7217
Black	Red	0.4223	0.4803	0.6369	0.6142
	Green	0.2532	0.3405	0.4406	0.5562
	Blue	0.1059	0.2921	0.3869	0.4849
	Yellow	0.1806	0.3293	0.4096	0.6913
White	Red	0.3082	0.3116	0.4049	0.6264
	Green	0.1854	0.3876	0.4121	0.5880
	Blue	0.8156	0.6222	0.6811	0.7135
	Yellow	0.6598	0.5805	0.4277	0.7398
Gray	Red	0.2682	0.5003	0.4287	0.5860
	Green	0.0807	0.3203	0.2915	0.5496
	Blue	0.7874	0.3326	0.6676	0.6345

Chapter 5 presents an extended analysis of the data from Study 2 that addresses the concerns noted in this chapter. Using multilevel modeling, multiple symbol characteristics were included in various models to determine which factors drive response times in the uncued condition and which drive response times in the cued condition. The identification of these characteristics for each condition is imperative for creating useful symbol design guidelines.

Chapter 5: Multilevel-Modeling

The classic analysis, the repeated-measures ANOVA used in Chapter 4, is well suited to analyze the impact of categorical factors on a continuous response (Hammond, McClelland, & Mumpower, 1980). In Study 1 and 2, for example, the analysis investigated the effects of cueing and target color on detection time. However, one drawback of the ANOVA is that it can only use categorical predictors. The analysis of covariance (ANCOVA) may extend the ANOVA by including a continuous person-level covariate, but this is only appropriate if interactions between categorical factors and continuous covariates do not exist.

Multi-level models (MLM) are a worthwhile alternative to ANOVAs to deal with hierarchy in data (Bryk &Raudenbush, 1992; Goldstein, 1991), such as in repeated measure and longitudinal designs, nested designs, and any complex mixed designs that include between-subject and within-subject factors. Additionally, in contrast to ANOVAs, MLMs can use any combination of categorical and continuous predictors (Hoffman & Rovine, 2007). As described in Chapter 4, Study 2 used a mixed-factor design with background as a between-subject factor and cueing and symbol color as within-subject categorical factors. As salience is a continuous predictor, I could not include it in the ANOVA directly. Instead I tested the effects of symbol color and made inferences about the relationship between salience and response times based upon the average salience of each color symbol. MLMs allow for the analysis of the effects of cueing and salience directly.

"The material contained in this chapter is in preparation for submission to a journal".

In addition to its ability to account for interactions between categorical and continuous factors, multilevel modeling also provides many other theoretical and statistical benefits. Theoretical benefits include the more accurate capture of reality and the ability to answer to questions about heterogeneity and group differences, specifically because it allows to analyze all the observations (e.g. all trials) that were obtained during data collection (Hoffman & Rovine, 2007). Statistical benefits entail greater power than aggregation because observations do not need to be averaged and the ability to explain more variance (Goldstein, 1991; Hox, 1995, Gould, 2016).

The current analyses use data from Study 2 to investigate three questions. First, I examined which of the four salience models (Saliency Toolbox, GBVS, Simpsal, Sigsal) best predicts response times. As noted in Chapter 4, each salience model failed to predict the correct ordering of response times across background colors. The Saliency Toolbox predicted the correct ordering for the white background and the Simpsal model predicted the correct ordering for the black background. This is both a theoretical and practical concern. First, the fact that the models provide both quantitatively and qualitatively different predictions suggest that, at least for the current displays, the salience models may be capturing salience at different spatial scales. Determining which model best accounts for response times in these types of tasks and displays is essential for providing sound advice to practitioners who may want to use salience models as a tool for predicting response times.

Second, a set of MLM analyses tested the hypotheses from Chapter 4, but using salience directly as a predictor. To make assumptions about salience in Chapter 4, I used symbol color as a predictor because the ANOVA required the predictor to be a categorical variable. These results, however, may not be completely accurate because salience was not directly included in the analyses. As illustrated by the salience profiles shown in Figures 8, 9 and 10, even though the symbols had different average salience values, the salience distribution of each color target overlapped one another. In other words, although the blue targets had the lowest average salience, it did not mean that there were not any blue target that were more salient than some of the yellow, green, or red targets. The current MLM analyses assessed whether the conclusions from Chapter 4 hold when salience is included in the model as a continuous factor.

Lastly, the current work examined which factors or combination of factors drive response times in the uncued and in the cued conditions. To investigate this question, I model response times from all three background-color conditions, with separate models for the uncued and cued conditions. If certain factors in a model predict response times across the three background colors used in the current study, the factors included in the model may be generalizable to other symbol sets and displays. If successful, the model may inform the development of customized symbol sets or may serve as a technique to help researchers or designers reliably estimate response times in cued and uncued visual search tasks.

Methods

Answering these questions required an expanded Study 2 data set that fully characterizes every symbol, in every image, for all three background colors. Using the four salience models reviewed in the introduction, I generated four salience maps for each of the 300 stimulus images. From these four sets of salience maps, I created four versions of each symbol's general salience profile and characterized each one by its average salience value, median, skew, excess kurtosis, and standard deviation. This means that every red symbol, for example, has the same average salience value, same median, same standard deviation, and so on. Rather than using the maximum salience ratio used in Study 1 and 2, calculated by dividing the symbol's maximum salience by the image's maximum salience, I used the maximum salience value, which is just the symbol's maximum salience. Although these values are highly correlated, the maximum salience values may be more useful in investigating difference between trials and background conditions.

I also created a measure of overlap that reflects the degree to which the salience profile of one color overlaps with the salience profiles of the other three colors. As an additional measures of discriminability, I used perceptual Euclidian distance (Gisjenji, Gevers,& Lucassen, 2009) to calculate the average PED between each color and the color of the other three symbols (PED_{Avg}) and the PED between each symbol color and the background color (PED_{BG}). Equation 1 calculated the weighted distance between the RGB values of two colors, e and u. The following weights were chosen based on tests conducted by Gijsenij and colleagues (2009) that account for different effects on the perceived color distance of each color channel, w_R= 0.2, w_R=0.79 and w_R=0.01.

$$\mathrm{PED}(\mathbf{e}_e, \mathbf{e}_u) = \sqrt{w_R(r_e - r_u)^2 + w_G(g_e - g_u)^2 + w_B(b_e - b_u)^2},$$

$$\text{where } w_R + w_G + w_B = 1. \quad \text{(Eq1).}$$

Each individual symbol was also characterized by its maximum salience value that was normalized with respect to the maximum possible salience value of the salience model, distance from the center of the display, and nearest neighbor distances. All available variables are summarized in Table 15. The following section, however, only focuses on specific variables that I suspected were most likely to predict response times.

Table 15

Parameters available for Analysis for Study 2 for the cued and uncued condition. In the third column, I indicate the factors that I believe will most strongly drive uncued and cued RT.

	Parameters	Predicted Effect on
	Mean	Uncued RT
	Median	Uncued RT
	Standard Deviation	Cued RT
General Symbol	Skew	
	Excess Kurtosis	
	Overlap	Cued RT
	PED_{Avg}	Cued RT
	PED_{BG}	Cued RT
Individual Symbol	Max. Salience Ratio	Uncued RT
	Maximum Salience	Uncued RT
	Distance from the center	Uncued RT & Cued RT
	Nearest Neighbor distances (1-6)	Uncued RT & Cued RT

Of the parameters listed in Table 15, I expected that some may drive response times in both the unuced and cued conditions. The location of the target within the display, for example, likely has a large effect on response times. Participants focused on the center of the screen before each trial, so it was expected that targets closest to the center of the display should elicit faster response times. Eccentricity effects are well documented in the literature, with response times and errors increasing as eccentricity increases (Carrasco, Evert, Chang & Katz, 1995; Sekuler & Ball, 1986).

Targets also differ in their clustering or proximity to nearby symbols. In some cases, a target may lie within a cluster of other symbols; in other cases, it may be more isolated. The nearest neighbor distance provides one measure of clustering. A small nearest neighbor distance indicates that the target lies in close proximity to one or more symbols. Here I calculated 1st through 6th nearest neighbor distances. The 1st nearest neighbor distance represents the distance between the target and the closest symbol; the 6th nearest neighbor distance represents the distance between the target and the 6th closest symbol. The response time for detecting a given target on a specific trial, then, may be affected based upon the number and proximity of nearby distractors, due to the effects of crowding, the phenomenon that perception is impaired when similar shapes are in close proximity of a target (Korte, 1923).

Certain variables may be more useful for modeling response times in the uncued condition than in the cued condition. Which of these variables predict response times in the uncued condition? The general pattern of results from Study 1 and Study 2 suggested that salience drives attention in the uncued condition. As uncued search should be exclusively driven by bottom-up mechanisms, the PED_{BG} may also predict uncued response times, as it is a measure of symbol-background contrast. The more similar the symbol is to its background, the more difficult it may be for the viewer to detect the target.

What drives response times in the cued condition? Results from Study 2 showed that target salience does not determine the magnitude of the cueing effect. If salience does not drive cued response time, then perhaps the shape of the salience profiles can provide an indication of a symbol's effectiveness as a cue. A symbol that has a narrower distribution (smaller standard deviation) may be a more effective because it is consistently high in salience or consistently low in salience. In contrast, a symbol with a wider distribution of salience values may indicate that the symbols' salience is strongly affected by its position within the display or the presence of surrounding clutter. Another factor that may determine the size of the cueing effect is a symbol's discriminability from other symbols. A symbol that is difficult to discriminate from another symbol in the same set would not allow the viewer to reduce the search set size as effectively as a symbol that was easy to discriminate from other symbols in the set. Symbol discriminability can be characterized by a symbol's average perceptual distance in color space to all other symbols (PED_{Avg}) and/or the measure of salience profile overlap

Multilevel models. MLMs distinguish between random effects and fixed effects. Random effects vary over all individuals. In this analysis, individuals are considered a random effect. Fixed effects, on the other hand, are specified as constant over all individuals such as cueing and salience. Below I present numerous multilevel-models that each attempt to predict response times using specific fixed factors. Specific fixed factors include salience, cueing, standard deviation, overlap, distances from the center, nearest neighbor distances, PED_{Avg} and $PED_{BG.}$

As in the previous analysis, the first ten trials for each participant served as practice trials and were excluded from the analysis. 51 trials with slow reaction times (>30s) were also excluded, representing 0.18% of all trials. All participants reached an accuracy level of 94% or higher, with 30 participants obtaining a score of 100%. This resulted in a total of 28,350 observations. Each multilevel model was 2-level random intercept model (Aguinis, Gottfredson, & Culpepper, 2013) because Level 2 stimuli factors were nested within participants at Level 1. Models used an unstructured covariance matrix using the lme function from the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2015) in R 3.2.2 (R Core Team, 2015). The ICC for the model suggested that response time was mildly clustered within participants, ICC = 0.07, p = 0.02. All R code is included in the Appendix B. The following section contains the results of 38 multilevel models that address three main purposes:

1. The first set of analyses assessed which salience model provides the best fit in the uncued condition in which top-down guidance is restricted. The purpose of these analyses is to select a salience model to use in all subsequent MLMs analyses.

2. The second set of analyses addressed the same hypotheses presented in Chapter 4. However, the use of MLMs allows me to test for the effect of salience directly instead of inferring the effect of salience by testing the effect of symbol color.
3. The final set of analyses examined whether any of the factors listed in Table 15 may serve as a better predictor of response times than salience, in both the uncued und cued conditions.

Analysis 1: Investigating Different Salience Models

MLM 1-4 assessed which salience model best predicts uncued response times. Each model contained salience values generated from only one salience model as a fixed effect, using only uncued data separated by background color. Maximum salience values for each salience model were normalized with respect to the maximum observed salience value across all images and backgrounds.

Results. The results of each model are listed in Table 16. The Saliency Toolbox Model (MLM1) revealed a significant effect of salience on response times for all three backgrounds, with response times decreasing as salience increased. The GBVS model (MLM2) and SigSal model (MLM4) both showed a significant effect of salience for the black and white backgrounds, with response times increasing as salience increased. For the gray background, the effect of salience was not significant. For the Simpsal model (MLM3), salience reached significance only for the black background, with response times increasing as salience increased.

Table 16

Fixed effects on RTs for Multilevel Model 1-4 that investigated the different salience models using only uncued data.

Model	Fixed Effect	b	SE	df	t	p	d
MLM 1a:	Intercept	4172.42	121.26	5030	34.41	< 0.01	
Black/ Sal.Toolbox	Salience	-525.84	155.08	5030	-3.40	< 0.01	-0.10
MLM 1b:	Intercept	5188.59	209.12	4450	24.81	< 0.01	
White/ Sal.Toolbox	Salience	-761.78	224.40	4450	-3.39	< 0.01	-0.10
MLM 1c:	Intercept	5689.83	246.20	4661	23.11	< 0.01	
Gray/ Sal.Toolbox	Salience	-1096.2	207.05	4661	-5.29	< 0.01	-0.16
MLM 2a:	Intercept	3824.07	126.44	5030	30.24	< 0.01	
Black/GBVS	Salience	393.15	154.22	5030	2.55	< 0.05	0.07
MLM 2b:	Intercept	4757.42	215.53	4450	22.07	< 0.01	
White/GBVS	Salience	444.48	213.89	4450	2.08	< 0.05	0.06
MLM 2c:	Intercept	5196.83	250.39	4661	20.75	< 0.01	
Gray/GBVS	Salience	165.13	218.71	4661	0.76	=0.45	0.02
MLM 3a:	Intercept	3755.16	139.73	5030	26.87	< 0.01	
Black/Simpsal	Salience	473.21	177.65	5030	2.66	< 0.01	0.08
MLM 3b:	Intercept	4863.28	224.45	4450	21.67	< 0.01	
White/Simpsal	Salience	169.85	234.68	4450	0.72	=0.47	0.02
MLM 3c:	Intercept	5387.52	253.34	4661	21.27	< 0.01	
Gray/ Simpsal	Salience	-273.26	230.96	4661	-1.18	=0.24	-0.04
MLM 4a:	Intercept	3601.60	155.26	5030	23.20	< 0.01	
Black/SigSal	Salience	657.37	188.64	5030	3.48	< 0.01	0.09
MLM 4b:	Intercept	4425.37	270.26	4450	16.37	< 0.01	
White/ SigSal	Salience	789.22	286.33	4450	2.79	< 0.01	0.08
MLM 4c:	Intercept	5396.49	287.74	4661	18.75	< 0.01	
Gray/ SigSal	Salience	-206.78	272.60	4661	-0.76	=0.45	-0.02

Discussion. Comparison of models based on each of the four different salience models revealed that only the Saliency Toolbox showed consistent effects across background colors, with response times decreasing as salience increased. This pattern of effects is consistent with the literature that shows that high salience targets should be detected faster in uncued search (Itti & Koch, 2001). The GBVS, Simpsal, and Sigsal model showed inconsistent relationships between salience and response time across background colors. Notably, these results are consistent with the results presented in Chapter 4 that showed that each salience model predicted a different ordering of symbol colors. The discrepancy in salience model output may suggest that the three salience models measure something different than the Saliency Toolbox model. One possibility is that the models may differ in the spatial scale at which they assess salience. For example, some models may differentiate between the salience of clusters of symbols and others may differentiate between the salience of individual symbols. Future work should investigate this hypothesis by manipulating the size and clustering of symbols to determine which model may serve as the best algorithm for assessing salience across a range of symbols and displays.

Although the Saliency Toolbox Models only showed small effects of salience ($d<0.2$), this model still produced the largest effect sizes of the four salience models and is therefore used in all further analyses.

Analysis 2: Extended Analysis from Chapter 4

MLM 5-8 examined the effect of cueing, salience and background color on response times using the complete data set including both cued and uncued conditions. This analysis tested the same hypotheses as the ANOVA in Chapter 4; however, instead of using symbol color to make assumptions about the effect of salience, the current analyses used salience directly as a predictor.

Results. Consistent with previous results; MLM 5 indicated a significant effect of cueing on response time, with faster response times for the cued condition (see Table 17). Salience also predicted response times. A non-significant interaction between cueing and salience indicated no differences in the salience effects between the uncued and cued conditions. The effect of salience on response time can be further characterized by a significant interaction between background and salience. For cued trials on the black background, response times increased with salience. For cued trials on the white and gray backgrounds, in contrast, response times decreased as salience increased.

The three-way interaction between cueing, salience, and background was also reliable. To further examine the nature of this interaction, the backgrounds were modeled separately in MLM 6 – 8.

Table 17

Fixed effects on RTs for Multilevel Model 5 using both cued and uncued trials. Cohen's d and partial R^2 reflect effect sizes.

MLM	Fixed Effect	b	SE	df	t	p	d	R^2
	Intercept	4089.83	84.48	28247	48.41	< 0.01		
	Cueing	-923.26	29.28	28247	-31.53	< 0.01	-0.38	0.09
	Salience	-720.22	67.02	28247	-10.75	< 0.01	-0.13	0.00
	Black BG	-689.19	117.79	91	-5.85	< 0.01	-1.2	0.16
	White BG	-231.18	120.58	91	1.92	= 0.06	0.40	0.14
	Cueing x Black BG	149.26	40.54	28247	3.68	< 0.01	0.03	0.00
	Cueing x White BG	56.53	41.44	28247	1.36	= 0.17	0.02	0.00
5	Salience x Cueing	62.05	67.00	28247	0.93	= 0.35	0.01	0.00
	Salience x Black BG	624.77	92.29	28247	6.72	< 0.01	0.08	0.00
	Salience x White BG	-327.30	98.86	28247	-3.32	< 0.01	-0.04	0.00
	Salience x Cueing x Black BG	366.11	92.29	28247	3.94	< 0.01	-0.04	0.00
	Salience x Cueing x White BG	-353.33	98.66	28247	-3.58	< 0.01	0.05	0.00

MLMs 6 to 8 further investigated this three-way interaction. Table 18 shows the fixed effects for each background color modeled separately. Across all three background models, cueing had a significant effect on response times, with faster response times for cued than uncued trials. However, as described below, the effect of salience and the interaction between salience and cueing was not consistent across backgrounds.

Table 18

Fixed effects on RTs for Multilevel Model 6-8 for uncued and cued data with each background modeled separately.

Model	Fixed Effect	b	SE	df	t	p	d
6: Black	Intercept	3400.48	87.61	9976	8.82	< 0.01	
	Cueing	-774.23	40.43	9976	-19.15	< 0.01	-0.38
	Salience	-95.29	92.81	9976	-1.03	= 0.30	-0.02
	Salience x Cueing	-428.53	92.85	9976	4.62	< 0.01	0.09
7: White	Intercept	4321.02	156.16	8867	27.67	< 0.01	
	Cueing	-866.82	53.72	8867	-16.14	< 0.01	-0.34
	Salience	-1047.56	132.70	8867	-7.89	< 0.01	0.17
	Salience x Cueing	-291.30	132.69	8867	-2.20	< 0.05	-0.05
8: Gray	Intercept	4548.14	184.50	9404	24.65	< 0.01	
	Cueing	-1129.23	58.07	9404	-19.44	< 0.01	-0.40
	Salience	-1017.95	121.95	9404	-8.35	< 0.01	-0.17
	Salience x Cueing	49.50	121.78	9404	0.41	= 0.68	0.01

For the black background (MLM6), salience alone did not influence response times. The interaction between salience and cueing, however, was significant. Response times increased as salience increased, but this effect was stronger in cued than uncued trials. For both the white background (MLM7) and the gray background (MLM8), salience showed a significant effect on response times, with response times decreasing as salience increased. However, for the white background, the interaction between salience and cueing was also significant, with response times decreasing as salience increased for both cued and uncued trials. In contrast, for the gray background (MLM8), the interaction between salience and cueing was not significant.

Overall, in the uncued condition, for the white and gray background, response times decreased as salience increased. On the black background, however, this relationship was not observed (see Figure 19).

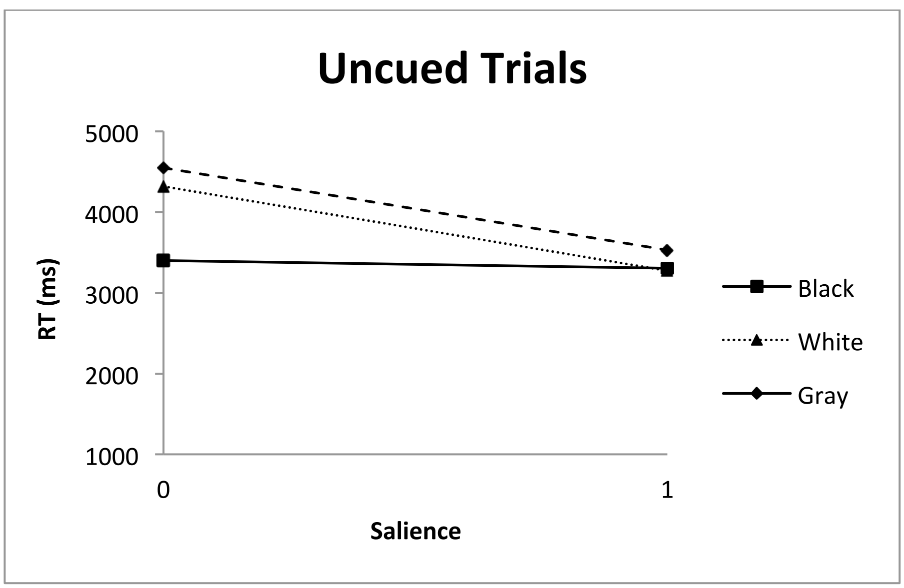

Figure 19. Model estimated RTs of each background color as a function of salience for uncued trials.

For the cued condition, response times increased as salience increased (see Figure 20) for the black background. For the white and gray background, however, this effect was reversed with response times decreasing as salience increased (see Figure 20).

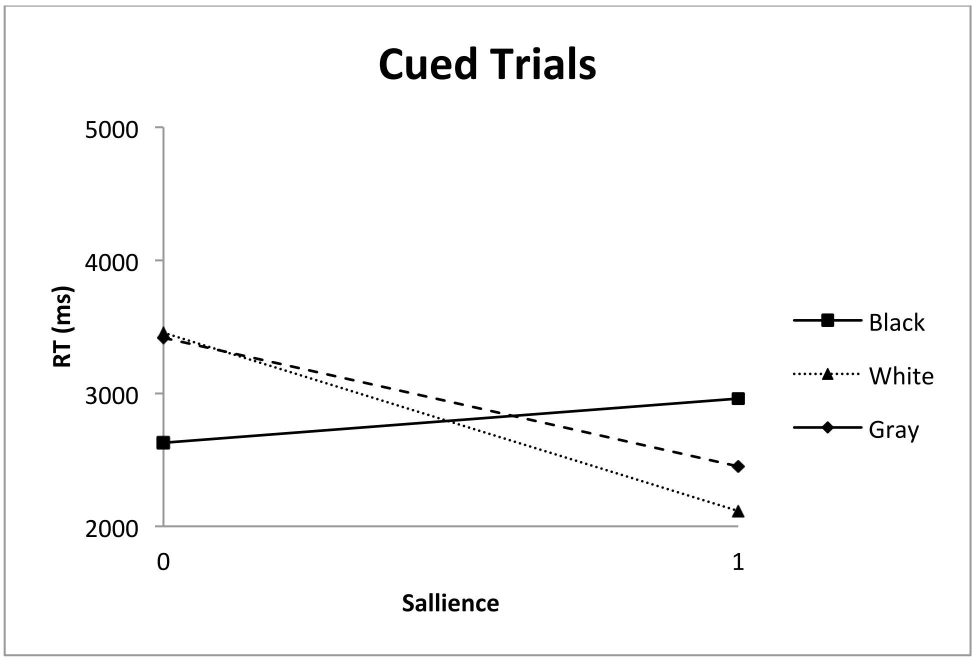

Figure 20. Model estimated RTs of each background color as a function of salience for cued trials.

Discussion. Analysis 2 tested the same hypotheses as the ANOVA in Chapter 4; however, instead of using symbol color to make assumptions about the effect of salience, the current analyses used salience directly as a predictor.

Consistent with previous results, response times were faster in the cued than in the uncued condition across background colors, indicating top-down feature guidance based on color. When the viewers knew the target color, they were able to find the target more quickly. The three-way interaction between cueing, salience and background was also reliable. This interaction was further investigated by modeling each background color separately. For the uncued condition, results showed that for the white and the gray BG, RTs decreased as salience increased. This is consistent with the analysis results from Study 2 that indicated that high salience symbols elicit faster response times than low salience symbols in uncued trials. This decrease in response times, however, was not as strong for the black background as it was for the white and the gray ones, suggesting that the sizes of the salience effects are context dependent. Although the relationship between salience and response time was not perfectly consistent across all background colors, the results generally support the hypothesis that high salience symbols elicit faster RTs than low salience symbols in the uncued condition in which search was driven exclusively by bottom-up factors.

Consistent with Study 2 results, in the cued condition, for the black background, response times increased as salience increased. For the white and the gray background, however, this effect was reversed, with response times decreasing as salience increases. The MLM analysis thus leads to the same conclusion presented in Chapter 4: the pattern of effects observed in the white and the gray background conditions do not support the hypothesis that low salience targets serve as more effective cues. These inconsistencies suggest that the size of the cueing benefit is driven by factors other than salience. The following MLMs therefore investigate additional target characteristics that may potentially serve as better predictors of response times in uncued and cued search.

Analysis 3: Investigating Other Factors Than Salience

MLM 5-8 showed that salience does not consistently predict uncued and cued response times across background. The following models, therefore investigated whether salience itself or other factors better predict response times in uncued and cued search. To be able to support the development of customized symbol sets that match performance goals and to generalize the results to other symbol sets, the models excluded background as a factor and modeled uncued and cued trials separately.

To investigate which factors best predicts response times in uncued search, uncued response times were modeled using maximum salience, standard deviation of the salience profile, overlap, the average PED (PED_{Avg}), background PED (PED_{BG}), a target's distance from the center and nearest neighbor distances as fixed effects. Each factor was modeled in a separate model, as shown in Table 19. For the cued condition, the same fixed factors were modeled separately, as shown in Table 21.

Results for uncued trials. Each MLM showed a significant effect for the fixed factor used in the model, except overlap (MLM11). Cohen's d indicates the biggest effects for d6, d5, d4 and dcenter, suggesting that clustering and eccentricity effects play a role in predicting response times. All models that used uncued data were compared against each other using the BIC. Results show no significant differences between models MLM 9 to MLM 20 for uncued trials, ($p>0.05$) BIC range from 272934 to 273121.

Table 19

Fixed effects on RTs for Multilevel Model 9- 20 only using uncued data.

Model	Fixed Effect	b	SE	df	t	p	d
MLM 9:	Intercept	4994.01	126.97	14143	39.33	< 0.01	
Salience	Salience	-791.837	11.32	14143	-7.05	< 0.01	0.12
MLM 10:	Intercept	6683.26	266.20	14143	24.94	< 0.01	
Std	Std	-6369.57	802.29	14143	-7.94	< 0.01	-0.13
MLM 11:	Intercept	4700.60	142.68	14143	32.94	< 0.01	
Overlap	Overlap	50.78	273.64	14143	0.19	= 0.85	0.00
MLM12:	Intercept	5023.07	172.94	14143	28.88	< 0.01	
PED_{Avg}	PED_{Avg}	-548.20	223.47	14143	-2.45	< 0.01	-0.04
MLM 13:	Intercept	5036.54	126.89	14143	39.69	< 0.01	
PED_{BG}	PED_{BG}	-655.61	98.67	14143	-6.64	< 0.01	-0.11
MLM 14:	Intercept	5647.50	143.92	14143	39.24	< 0.01	
Dcenter	dcenter	-2.72	0.23	14143	-11.77	< 0.01	-0.20
MLM 15:	Intercept	5269.78	138.11	14143	38.16	< 0.01	
D1	D1	-6.59	0.81	14143	-8.18	< 0.01	-0.14
MLM 16:	Intercept	5494.17	146.12	14143	37.60	< 0.01	
D2	D2	-6.43	0.68	14143	-9.39	< 0.01	-0.16
MLM 17:	Intercept	5705.81	152.92	14143	37.31	< 0.01	
D3	D3	-6.51	0.62	14143	-10.50	< 0.01	-0.18
MLM 18:	Intercept	5904.30	157.88	14143	37.40	< 0.01	
D4	D4	-6.64	0.57	14143	-11.62	< 0.01	-0.20
MLM 19:	Intercept	6062.47	161.42	14143	37.56	< 0.01	
D5	D5	-6.61	0.53	14143	-12.49	< 0.01	-0.21
MLM 20:	Intercept	6261.04	164.84	14143	37.98	< 0.01	
D6	D6	-6.82	0.50	14143	-13.69	< 0.01	-0.23

MLM21 modeled all significant factors from Table 19 for uncued trials, resulting in 11 fixed factors (salience, Std, PED_{Avg}, PED_{BG}, dcenter, d1, d2, d3, d4, d5, d6). All models and their fixed effects are depicted in Table 20. Results show significant effects for salience, standard deviation, dcenter, d1 and d6.

MLM22 dropped PED_{Avg}, PED_{BG} and d2-d5 resulting in 5 fixed effects (salience, standard deviation, dcenter, d1 and d6). Results show significant effects of all fixed factors, with salience showing the lowest effect size (d=-0.04).

MLM23 dropped salience as a fixed effect resulting in 3 fixed effects (dcenter, d1 and Std). MLM23 showed significant effects for all fixed factors, with standard deviation having the largest effect size. Unexpectedly, as the standard deviation increases, response times decrease.

Comparing MLM23 to all other models using uncued data (MLM9-22) showed a significant difference between models ($p<0.05$), with MLM23 having the lowest BIC out of all models, BIC ranging from 272865 – 273121. Overall, the combination of standard deviation, distance from the center and nearest neighbor distances resulted in the best prediction of response times but still only explained 2.6% of the variance (marginal R^2=0.026). This combination of fixed factors and the random effect of participants explained 10% of the variance (conditional R^2=0.104). In comparison, a model with only uncued trials and salience as a fixed factor explained less than 1% of variance (marginal R^2=0.004).

Table 20

Fixed effects on RTs for Multilevel Model 21-23 using uncued data.

Model	Fixed Effect	b	SE	df	t	p	d
	Intercept	8471.17	470.67	14133	18.00	< 0.01	
	Salience	-557.01	213.34	14133	-2.61	< 0.01	-0.04
MLM	Std	-6882.71	1692.24	14133	-4.07	< 0.01	-0.07
21	PED_{Avg}	60.87	269.71	14133	0.23	= 0.82	0.00
	PED_{BG}	461.68	245.17	14133	1.88	=0.06	0.03
	dcenter	-1.40	0.28	14133	-5.04	< 0.01	-0.09
	D1	-3.30	1.12	14133	-2.94	< 0.01	-0.05
	D2	-0.44	1.35	14133	-0.33	= 0.74	-0.00
	D3	0.30	1.53	14133	0.19	= 0.85	-0.00
	D4	-0.59	1.66	14133	-0.36	= 0.72	-0.01
	D5	1.67	1.80	14133	0.93	= 0.35	0.02
	D6	-5.33	1.38	14133	-3.87	< 0.01	-0.07
MLM	Intercept	7922.38	337.78	14139	23.45	< 0.01	
22	Salience	-373.64	155.24	14139	-2.41	< 0.05	-0.04
	Std	-4420.71	1104.84	14139	-4.00	< 0.01	-0.07
	dcenter	-1.44	0.27	14139	-5.19	< 0.01	-0.09
	D1	-3.26	0.89	14139	-3.69	< 0.01	-0.06
	D6	-4.29	0.64	14139	-6.68	< 0.01	-0.11
MLM	Intercept	8434.42	288.78	14140	28.89	< 0.01	
23	Std	-6272.54	796.95	14140	-7.87	< 0.01	-0.13
	dcenter	-1.49	0.28	14140	-5.41	< 0.01	-0.09
	D1	-2.95	0.88	14140	-3.37	< 0.01	-0.05
	D6	-4.29	0.64	14140	-6.68	< 0.01	-0.11

Discussion. Various MLMs investigated a variety of symbol characteristics besides salience that may predict response times. For uncued trials, MLMs with only one fixed factor showed that distance from the center and nearest neighbor distances predicted response times, consistent with eccentricity effects (Sekuler & Ball, 1986) and crowding effects (van den Berg, Roerdink, & Cornelissen, 2007) that are typically observed in visual search tasks. MLMs that included more than one fixed factor confirmed the importance of distance from the center, nearest neighbor distances 1 and 6 and standard deviation of a symbol's salience profile in predicting response time. Interestingly, d6 showed a bigger effect size than d1 indicating that only including the 6^{th} nearest neighbor distance may suffice. Out of these four factors, the standard deviation of the salience profile showed the strongest effect in predicting response times, with response times decreasing as the standard deviation of the target colors' salience profile increases. In other words, symbol colors that had a wider range of salience values were found more quickly. Although, I hypothesized that the shape of the salience profiles may provide an indication of a symbol's cueing benefit, I did not expect this relationship between the standard deviation of the salience profile and uncued response times. At this point, I am uncertain of what this finding may reflect. I considered whether this effect resulted from a strong correlation between standard deviation and the mean of the salience profile. Although, these two factors were highly correlated ($r = 0.9$), the mean of the salience profile did not significantly predict uncued response times ($p = 0.11$).

However, out of all these models, the best model (MLM23) only explained about 2.5% of the variance, with only small effect sizes ($d<0.02$) for each fixed factor. One reason for these small effect sizes may be that these MLMs excluded the background as a factor in order to be able to generalize the results beyond this symbol set and display. However, after including the background color as a factor, results also showed small effect sizes ($d<0.02$).

Results for cued trials. Results show a significant effect for salience (MLM 24), overlap (MLM 26), PED_{Avg} (MLM 27), dcenter (MLM29) and d1-d6 (MLM 30-35). Only standard deviation in MLM 25 and PED_{BG} in MLM 28 show no significant effect on response times. PED_{Avg} shows the biggest effect size, yet it remains small ($d=-0.23$).

All models that used cued data were compared, resulting in no significant difference between models ($p>0.05$), BIC range from 256,848 to 257,031. To investigate whether multiple factors model response times more effectively and account for more variance, MLMs with multiple fixed factors were conducted.

Table 21

Fixed effects on RTs for Multilevel Model 24-35 only using cued data.

Model	Fixed Effect	b	SE	df	t	p	d
MLM 24:	Intercept	3140.77	71.38	14017	44.00	< 0.01	
Salience	Salience	-600.11	69.96	14017	-8.58	< 0.01	-0.14
MLM 25:	Intercept	3042.12	164.01	14017	18.55	< 0.01	
Std	Std	-379.45	469.37	14017	-0.76	= 0.44	-0.01
MLM 26:	Intercept	2520.63	83.36	14017	30.24	< 0.01	
Overlap	Overlap	1443.04	171.40	14017	8.42	< 0.01	0.14
MLM 27:	Intercept	3981.71	102.39	14017	38.89	< 0.01	
PED_{Avg}	PED_{Avg}	-1871.54	137.67	14017	-13.59	< 0.01	-0.23
MLM 28:	Intercept	2986.83	73.25	14017	40.78	< 0.01	
PED_{BG}	PED_{BG}	-120.90	61.68	14017	-1.96	= 0.05	-0.03
MLM 29:	Intercept	2797,56	83.32	14017	33.58	< 0.01	
Dcenter	dcenter	0.38	0.14	14017	-2.62	< 0.01	0.04
MLM 30:	Intercept	3168.54	79.37	14017	39.92	< 0.01	
D1	D1	-2.87	0.51	14017	-5.66	< 0.01	-0.10
MLM 31:	Intercept	3118.15	84.44	14017	39.32	< 0.01	
D2	D2	-1.58	0.43	14017	-3.71	< 0.01	-0.06
MLM 32:	Intercept	3121.77	89.067	14017	35.05	< 0.01	
D3	D3	-1.23	0.39	14017	-3.31	< 0.01	-0.06
MLM 33:	Intercept	3120.22	92.05	14017	33.90	< 0.01	
D4	D4	-1.08	0.35	14017	-3.05	< 0.01	-0.05
MLM 34:	Intercept	3107.95	94.53	14017	32.88	< 0.01	
D5	D5	-0.89	0.33	14017	-2.71	< 0.01	-0.05
MLM 35:	Intercept	3092.00	96.70	14017	31.98	< 0.01	
D6	D6	-0.73	0.31	14017	-2.36	< 0.05	-0.04

MLM 36 modeled all significant factors from Table 21 for cued data, resulting in 10 fixed factors (salience, overlap, PED_{Avg}, dcenter, d1-6). All models and their fixed effects are displayed in Table 22. Results show significant effects for all fixed factors, with overlap showing the smallest effect size (d=0.04).

MLM 37 dropped d2-d6 as fixed factors, resulting in 5 fixed factors (salience, PED_{Avg}, Overlap, dcenter, d1). MLM 37 showed significant effects for all fixed factors, with overlap showing the smallest effect size (d = -0.04). Comparing MLM 27 to MLM 26 results in a slightly better model fit ($p<0.05$).

MLM38 dropped overlap as a factor, resulting in 4 fixed factors (salience, PED_{Avg}, dcenter, d1). All factors reached significance, with the highest effect size for PED_{Avg} (d=-0.18).

Comparing MLM38 to all other models that used cued data only (MLM 24-37) resulted in the best model fit for MLM 38 ($p < 0.05$), BIC range 256816 – 257031. The combination of salience, PED_{Avg}, decenter and d1 results in the best model, but only explained 1.6% of the variance (marginal R^2=0.016). This combination of fixed factors and the random effect of participants explained about 9% of the variance (conditional R^2=0.092).

Table 22

Fixed effects on RTs for Multilevel Model 36-38 using cued data.

Model	Fixed Effect	b	SE	df	t	p	d
MLM	Intercept	3934.25	155.18	14008	25.35	< 0.01	
36	Salience	-282.89	80.09	14008	-3.53	< 0.01	-0.06
	PED_{Avg}	-1480.95	163.94	14008	-9.03	< 0.01	-0.15
	Overlap	405.47	192.65	14008	2.10	< 0.05	0.04
	Dcenter	0.83	0.17	14008	4.76	< 0.01	-0.08
	D1	-3.02	0.70	14008	-4.34	< 0.01	-0.07
	D2	0.52	0.82	14008	0.63	= 0.53	-0.01
	D3	-0.26	0.95	14008	-0.27	= 0.79	-0.00
	D4	-0.29	1.04	14008	-0.28	= 0.78	-0.00
	D5	-0.19	1.11	14008	-0.17	= 0.86	-0.00
	D6	-0.07	0.84	14008	-0.79	= 0.43	-0.01
MLM	Intercept	3830.27	149.71	14013	25.58	< 0.01	
37	Salience	-282.16	79.94	14013	-3.53	< 0.01	-0.06
	PED_{Avg}	-1479.68	163.89	14013	-9.03	< 0.01	-015
	Overlap	406.12	192.63	14013	2.11	< 0.05	-0.04
	Dcenter	0.59	0.15	14013	4.06	< 0.01	-0.09
	D1	-3.42	0.52	14013	-6.63	< 0.01	-0.11
MLM	Intercept	4022.14	118.74	14014	33.87	< 0.01	
38	Salience	-311.35	78.74	14014	-3.95	< 0.01	-0.07
	PED_{Avg}	-1589.14	153.98	14014	-10.38	< 0.01	-0.18
	Dcenter	0.60	0.15	14014	4.10	< 0.01	-0.07
	D1	-3.45	0.52	14014	-6.68	< 0.01	-0.11

Discussion. The following models investigated whether multiple fixed factors predicted response times in cued trials. MLMs with one fixed factor showed that salience, overlap, $PED_{Avg,}$ distance from the center and nearest neighbor distances play a role in predicting cued response times. Models with multiple fixed effects confirmed that the best predictors of cued response times are PED_{Avg}, salience, distance from the center and the first nearest neighbor distance, explaining about 1.6 % of the variance. As PED_{Avg} was one of the best predictors of response time, the results suggest that symbol-symbol discriminability is particularly important in cued search. Symbols that can be discriminated from other symbols are a more effective cue leading to faster response times. Our measure of discriminability, PED_{Avg}, may be an easy-to-use tool that does not require any specialized software. Notably, the response time benefit found for the blue symbol in Study 2 across all backgrounds may be explained with the PED_{Avg} values. The blue symbol is farthest away in perceptual color space, making it on average easier to discriminate from other symbols. As illustrated in Figure 21, the PED_{Avg} values are not dependent upon the background color, with nearly identical effects of PED_{Avg} on response times across backgrounds. While PED_{Avg} may predict response times quite well, the different slopes suggest that the salience of the target still plays a role in predicting response times, particularly for targets that are close together in perceptual color space.

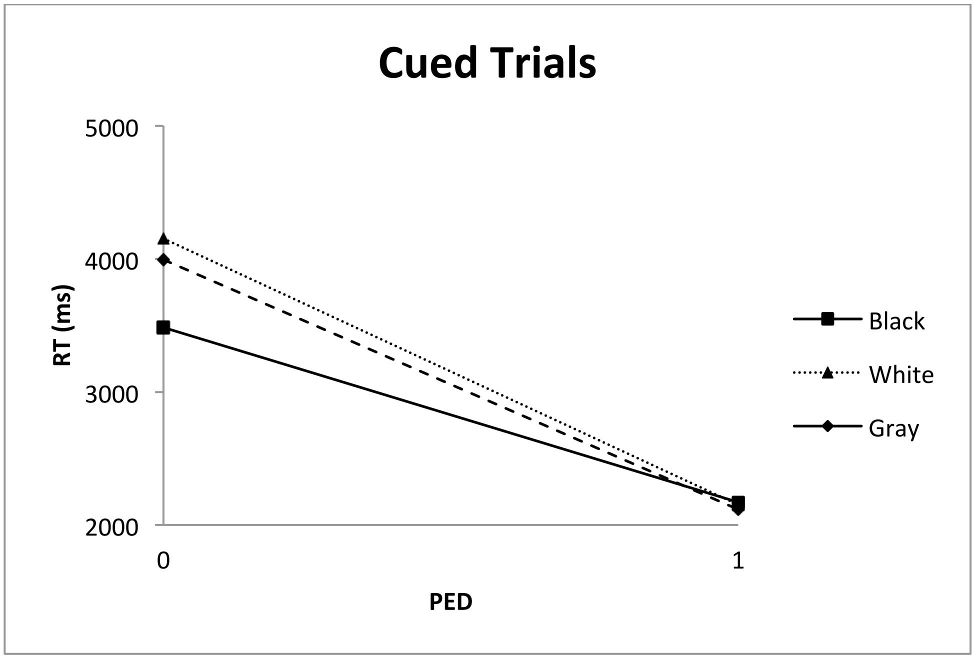

Figure 21. Model estimated RTs of each background color as a function of PED_{Avg} for cued trials. A PED_{Avg} of 1 indicates high discriminability with a symbol being farther away from another symbol in color space.

Chapter 6: Conclusion

The current project had one theoretical and one applied goal. First, I wanted to investigate and understand the interaction of bottom-up and top-down mechanisms in visual search tasks. Second, I wanted to use that knowledge to help develop design guidelines for customized symbol sets for effective displays that support specific tasks and performance goals.

Chapter 3 presented an experiment that used the flicker paradigm to investigate the effects of top-down and bottom-up control in a change detection task. I created a customized symbol set, containing four different colored squares as symbols on a black background. A cueing manipulation isolated top-down effects to the cued condition. For uncued trials, high salience symbols produced the fastest response times. For cued trials, results showed a response time benefit for low salience symbols on a black background, consistent with Orchard (2012) and Steelman et al. (2013).

Chapter 4 used the same paradigm, but added two different background colors to investigate whether the benefit for low salience symbols was an artifact of the black background. As salience is dependent on a target's contrast relative to its surroundings (Itti & Koch, 2001; Wolfe & Horrowitz, 2004), the background manipulation changed each symbol's salience, while preserving the symbol's color and location. Data was analyzed using SPSS's repeated-measures ANOVA with symbol color as within-subject factor and background as a between-subject factor. For uncued trials, participants generally detected high salience symbols faster than low salience symbols. These results

"The material contained in this chapter is in preparation for submission to a journal".

are consistent with the literature that shows that high salience targets should be detected faster in bottom-up search tasks (Itti & Koch, 2001). The benefit of low salience symbols on cued response times was replicated, however, only on the black background. Results from the white and the gray background did not support this hypothesis. The blue symbol showed the fastest cued response times across conditions, despite being the lowest salience target in one condition and the highest salience target in the others. The results suggest that it must be some other characteristic of the blue symbol that drives its cueing benefit.

Chapter 5 extended the analyses from Chapter 4 using various multilevel models to (1) compare the utility of four different salience models' algorithms in predicting response times in uncued search, (2) directly test the hypothesis that target salience predicts response times, and (3) determine how other symbol characteristics besides salience may influence response times in uncued and cued search.

The comparison of the four salience models revealed different relationships between the salience and response times for each model. These differences between the models most likely indicate that certain models may be more sensitive to the salience of clusters of symbols than the salience of an individual symbol.

The results of the MLM analyses generally supported the hypothesis that high salience symbols elicit faster response times than low salience symbols in the uncued condition. However, consistent with Chapter 4, response times for the cued condition did not support the hypothesis that low salience targets serve as more effective cues across backgrounds. Instead, the blue symbol was the most effective cue as a high salience symbol and as a low salience symbol across conditions, suggests that other factors characteristics besides salience drive cued response times.

The analyses to determine how other symbol characteristics besides salience may influence response times found that distance from the center and nearest neighbor distances significantly predicted response times in both uncued and cued conditions. Consistent with eccentricity effects typically observed in visual search tasks (Sekuler & Ball, 1986), response times were faster for targets located closer to the center of the display. The relationship between nearest neighbor distances is consistent with crowding effects (Korte, 1923). Crowding may impair the discrimination of objects and the ability to accurately respond to the object in clutter (van den Berg, Roerdink, & Cornelissen, 2007; Whitey & Levi, 2012). A target that is part of a cluster, therefore, may not be detected or detected more slowly than a target that is farther located from its neighbors.

In uncued search, results from the original analyses (Chapter 3 & 4) indicate an effect of salience, with high salience targets being detected faster than low salience targets, which is consistent with the literature (Itti & Koch, 2001). Results of the MLM analysis, however, indicated that the standard deviation of the salience profile showed the strongest effect in predicting response times, with response times decreasing as the standard deviation of the target colors' salience profile increases. In other words, symbol colors that had a wider range of salience values tended to be found more quickly.

Although I hypothesized that the shape of the salience profiles may provide an indication of a symbol's cueing benefit, I did not expect this relationship between the standard deviation of the salience profile and uncued response times. At this point, I am uncertain of what this finding may reflect.

In cued search, the results from the previous chapters indicated that PED_{Avg} plays a role in predicting response times. As illustrated in Figure 21, PED_{Avg} was an effective predictor for cued response times across conditions. However, the different slopes indicated that salience still played an important role in predicting cued response times. Thus, the combination of salience and PED_{Avg} may serve as a good predictor of cued response times.

Although all these factors reached significance in the analyses of the uncued and cued condition, they explained less than 2% of the variance (MLM23 and MLM36). The difference in participants explained the most variance, leading to a total of 10% including fixed and random effects. The results of this work suggest the following recommendations for effective display design.

In guided and unguided search, the target's distance from the center and the nearest neighbor distances influence response times. Results of the MLM analyses indicated that the response time for detecting a given target on a specific trial might be affected by both the number and proximity of nearby distractors due to the effects of crowding and clustering. These findings are consistent with eccentricity effects (Sekuler & Ball, 1986) and crowding effects (Korte, 1923; van den Berg, Roerdink, & Cornelissen, 2007) found in the literatures. Crowding, for example, may impair the discrimination of objects and the ability to accurately respond to an object in clutter (Whitey & Levi, 2012). A target that is part of cluster, therefore, may not be detected or detected more slowly than a target that is farther located from its neighbors. If a task requires the operator to detect an entity accurately and rapidly, then this entity should be placed on the center of the display free of clutter. For example, if the location of an important onset such as a visual alert can be controlled, then it should be located near the center of the display to promote faster detection. Although it may not always be possible to control the location of entities as in many supervisory monitoring tasks, knowing that eccentricity and crowding may influence response times can be useful for training operators to prioritize scanning peripheral regions within the display or areas of dense clutter.

In unguided search or when viewers may or may not know specifically what they are looking for within a display, salience should be considered when assigning identities to symbols. If the task requires the rapid detection of a particular entity (such as an enemy or suspected enemy), then that entity should be deliberately assigned to the most salient symbol within the symbol set to support the most rapid detection. Notably, it is important to consider not only the design of individual symbols, but the design of the entire set as salience is dependent on a target's contrast relative to its surroundings (Wolfe & Horrowitz, 2004). This means that all other symbols need to be considered as well as the background upon which the symbol will be placed on. As illustrated in Chapter 4, different colored backgrounds change a symbol's salience profile, such that a symbol that is highly salient when placed on one background may not be salient when placed on another background, even when the color and locations of surrounding symbols remain fixed. This implies that designer should anticipate that the performance characteristics of a symbol set may vary across displays and applications. The detection of a blue emergency telephone, for example, may be very different on a green background on a recreational park map than on a white background city map.

In guided search, symbol sets should be designed to maximize the discriminability of targets. As demonstrated in Chapter 5, symbols that can be more easily discriminated (larger PED_{Avg}) from other symbols tend to be more effective cues, leading to faster response times. If the task requires the operator to prioritize the detection of a particular entity, then this entity should be assigned to the symbol with the largest PED_{Avg} value within the symbol set. If all entities have equal priority, the symbol set should be designed such that the symbols are equally spaced in perceptual color space. Although color typically plays a larger role in the discriminability of targets (Steelman et al., 2013), there are other features such as shape and size that may also influence the discriminability of targets.

Although I have provided specific recommendations about the characteristics that may influence response times, these recommendations must be qualified. As the analyses in Chapter 5 demonstrated, despite their statistical significance within the models, these factors accounted only for a small amount of variance in the data. In order to develop more specific guidelines for designers, additional work is necessary to identify other factors that may serve as good predictors of response times in cued and uncued search tasks. Despite this qualification, the current work provides a systematic attentional approach that can be used to identify key design features to support the creation of customized symbol sets that match performance goals.

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Appendix A

This documentation is for Figure 1. The material used to create Figure 1 arrived from the Department of Defense (D. O. D.,2008) which lies in the public domain and has been approved for public distribution (see screenshot below).

DEPARTMENT OF DEFENSE
INTERFACE STANDARD

COMMON WARFIGHTING SYMBOLOGY

Distribution A: Approved for public release, distribution is unlimited.

Appendix B

```
library(nlme)
library(visreg)
library(MuMIn)
dataset <- read.csv("~/Desktop/finalreduced062016.csv", sep=";", dec=",
")
dataset$NewSub=factor(dataset$NewSub)

##### Effect Coding ###########

### CuedorUncued
# z=CuedorNot original, z.e1: cued=1, uncued=-1
dataset <- within( dataset, {
  z <- CuedOrNot
  cueing <- ifelse( CuedOrNot=="1", 1,
                    ifelse( CuedOrNot=="0", -1, NA ) )
})
#### Background
#1=Black, 2=White, 3=Gray
dataset <- within( dataset, {
  a <- Session
  black <- ifelse( Session=="1", 1,
                   ifelse( Session=="2", 0,
                           ifelse( Session=="3", -1, NA  ) ) )
  white <- ifelse(Session=="1", 0,
                  ifelse( Session=="2", 1,
                          ifelse( Session=="3", -1, NA ) ) )

})
########### Normalize PED and PEDBG ##########
dataset <- within (dataset,{
  BGPEDn <- (BGPED/255)
})
dataset <- within (dataset,{
  PEDn <- (MeanPED/255)
})
#Normalize salience values

dataset <- within (dataset,{
  SalMax1n <- (SalMax1/2.4533)
})
dataset <- within (dataset,{
  SalMax2n <- (SalMax2/1)
})
```

```
dataset <- within (dataset,{
  SalMax4n <- (SalMax4/1.05076)
})
dataset <- within (dataset,{
  SalMax3n <- (SalMax3/1)
})
dataset <- within (dataset,{
  SalMax5n <- (SalMax5/1.0162)
})

# If we only want to use cued or uncued responses, within the selected
background

#black

cuedonlyblack <- subset(blackonly, cueing >0 ) # data with only cued re
sponses

uncuedonlyblack <- subset(blackonly,cueing < 0) #data only uncued

#white

cuedonlywhite <- subset(whiteonly, cueing >0 ) # data with only cued re
sponses

uncuedonlywhite <- subset(whiteonly,cueing < 0) #data only uncued

#gray

cuedonlygray <- subset(grayonly, cueing >0 ) # data with only cued resp
onses

uncuedonlygray <- subset(grayonly,cueing < 0) #data only uncued

#select uncued and cued, all BG colors

cuedonly <- subset(dataset, cueing >0 ) # data with only cued responses

uncuedonly <- subset(dataset,cueing < 0) #data only uncued

# If we only want to use one BG, separate data

blackonly <- subset(dataset, Session ==1 ) # data with only black

whiteonly <- subset(dataset, Session ==2 ) # data with only white

grayonly <- subset(dataset, Session ==3 ) # data with only gray

#ICC baseline model with no predictors

baseline.model <- lme( RT ~ 1, random=~1|NewSub, na.action = "na.exclud
e", data=dataset )
```

```
summary( baseline.model ) #have to sqaure random effect stddev and resi
dual.

#std^2 / std^2 + residual^2 in random effects

ICC <- 841.8011*841.8011/ (841.8011*841.8011+3067.71*3067.71)

ICC #0.07

rICC <- sqrt(((43.10829)^2)/(((43.10829)^2)+28256))

rICC

#################### INVESTIGATE SALIENCE MODELS ####################
####

# MODEL 1

model1bu <- lme( RT ~ SalMax1n, method="ML", random=~1|NewSub, data=unc
uedonlyblack ) #method ML then anova works'

summary(model1bu)

model1wu <- lme( RT ~ SalMax1n, method="ML", random=~1|NewSub, data=unc
uedonlywhite ) #method ML then anova works'

summary(model1wu)

model1gu <- lme( RT ~ SalMax1n, method="ML", random=~1|NewSub, data=unc
uedonlygray ) #method ML then anova works'

summary(model1gu)

# MODEL 2

model2bu <- lme( RT ~ SalMax2n, method="ML", random=~1|NewSub, data=unc
uedonlyblack ) #method ML then anova works'

summary(model2bu)

model2wu <- lme( RT ~ SalMax2n, method="ML", random=~1|NewSub, data=unc
uedonlywhite ) #method ML then anova works'

summary(model2wu)

model2gu <- lme( RT ~ SalMax2n, method="ML", random=~1|NewSub, data=unc
uedonlygray ) #method ML then anova works'

summary(model2gu)

# MODEL 3
```

```
model3bu <- lme( RT ~ SalMax4n, method="ML", random=~1|NewSub, data=unc
uedonlyblack ) #method ML then anova works'

summary(model3bu)

model3wu <- lme( RT ~ SalMax4n, method="ML", random=~1|NewSub, data=unc
uedonlywhite ) #method ML then anova works'

summary(model3wu)

model3gu <- lme( RT ~ SalMax4n, method="ML", random=~1|NewSub, data=unc
uedonlygray ) #method ML then anova works'

summary(model3gu)

# MODEL 4

model4bu <- lme( RT ~ SalMax5n, method="ML", random=~1|NewSub, data=unc
uedonlyblack ) #method ML then anova works'

summary(model4bu)

model4wu <- lme( RT ~ SalMax5n, method="ML", random=~1|NewSub, data=unc
uedonlywhite ) #method ML then anova works'

summary(model4wu)

model4gu <- lme( RT ~ SalMax5n, method="ML", random=~1|NewSub, data=unc
uedonlygray ) #method ML then anova works'

summary(model4gu)

rbu1 <- sqrt(((-3.40)^2)/(((-3.40)^2)+5030))

rbu1

dbu1<- (2*(-3.40))/sqrt(5030)

dbu1

rwu1 <- sqrt(((-3.39)^2)/(((-3.39)^2)+4450))

rwu1

dbu1<- (2*(-3.40))/sqrt(5030)

dbu1

dwu1<- (2*(-3.39))/sqrt(4450)

dwu1

dgu1<- (2*(-5.29))/sqrt(4461)
```

```
dgu1
rgu1 <- sqrt(((-5.29)^2)/(((-5.29)^2)+4461))
rgu1
dgu1<- (2*(-5.29))/sqrt(4461)
dgu1
#model2
rbu2 <- sqrt(((2.55)^2)/(((2.55)^2)+5030))
rbu2
rwu2 <- sqrt(((2.08)^2)/(((2.08)^2)+4450))
rwu2
rgu2 <- sqrt(((0.76)^2)/(((0.76)^2)+4461))
rgu2
dbu2<- (2*(2.55))/sqrt(5030)
dbu2
dwu2<- (2*(2.08))/sqrt(4450)
dwu2
dgu2<- (2*(0.76))/sqrt(4461)
dgu2
#model3
rbu3 <- sqrt(((2.66)^2)/(((2.66)^2)+5030))
rbu3
rwu3 <- sqrt(((0.72)^2)/(((0.72)^2)+4450))
rwu3
rgu3 <- sqrt(((-1.18)^2)/(((-1.18)^2)+4461))
rgu3
dbu3<- (2*(2.66))/sqrt(5030)
dbu3
```

```
dwu3<- (2*(0.72))/sqrt(4450)

dwu3

dgu3<- (2*(-1.18))/sqrt(4461)

dgu3

#model4

rbu4 <- sqrt(((3.28)^2)/(((2.48)^2)+5030))

rbu4

rwu4 <- sqrt(((2.79)^2)/(((2.79)^2)+4450))

rwu4

rgu4 <- sqrt(((-0.76)^2)/(((-0.76)^2)+4461))

rgu4

dbu4<- (2*(3.28))/sqrt(5030)

dbu4

dwu4<- (2*(2.79))/sqrt(4450)

dwu4

dgu4<- (2*(-0.76))/sqrt(4461)

dgu4

############## ANALYSIS LIKE CHAPTER 4, SALIENCE AS PREDICTOR #########

#salience, cueing and BG, plus interactions, HFES version

model14a <- lme( RT ~ SalMax1n+cueing+black+white+cueing*black +cueing*
white+

                   cueing*SalMax1n+white*SalMax1n+black*SalMax1n+cueing
*SalMax1n*white+cueing*SalMax1n*black, random=~1|NewSub, method= "ML",
data=dataset ) #method ML then anova works'

summary(model14a)

anova(model14a)

#salience. r

#cueing  r

# black R2, r
```

```
r.squaredGLMM(model14a)

#effect sizes salience

rsalience <- sqrt(((-10.74679)^2)/(((-10.74679)^2)+28247))

dsalience<- (2*(-10.74679))/sqrt(28247)

dsalience

r2salience <- ((1/28247)*117.6020)/(1+(1/28247)*117.6020)

r2salience

#cueing

rcueing <- sqrt(((-31.53199)^2)/(((-31.53199)^2)+28247))

dcueing<- (2*(-31.53199))/sqrt(28247)

dcueing

r2cueing <- ((1/28247)*2642.3488)/(1+(1/28247)*2642.3488)

r2cueing

#black

rblack <- sqrt(((-5.85065)^2)/(((--5.85065)^2)+91))

dblack<- (2*(-5.85065))/sqrt(91)

dblack

r2black <- ((1/91)*17.3589)/(1+(1/91)*17.3589)

r2black

dwhite<- (2*(1.91718))/sqrt(91)

dwhite

r2white <- ((1/91)*1.2584)/(1+(1/91)*1.2584)

r2white

r2cueingblack <- ((1/28247)*135.6328)/(1+(1/28247)*135.6328)

r2cueingblack

dcb<- (2*(2.68176))/sqrt(28247)

dcb
```

```
r2cueingwhite <- ((1/28247)*5.8321)/(1+(1/28247)*5.8321)

r2cueingwhite

dcw<- (2*(1.36403))/sqrt(28247)

dcw

r2sc <- ((1/28247)*1.6846)/(1+(1/28247)*1.6846)

r2sc

dsc<- (2*(0.92613))/sqrt(28247)

dsc

r2sw <- ((1/28247)*0.1312)/(1+(1/28247)*0.1312)

r2sw

dsw<- (2*(-3.31683))/sqrt(28247)

dsw

r2sb <- ((1/28247)*44.29)/(1+(1/28247)*44.29)

r2sb

dsb<- (2*(6.72401))/sqrt(28247)

dsb

r2scw <- ((1/28247)*3.0440)/(1+(1/28247)*3.0440)

r2scw

dscw<- (2*(-3.58123))/sqrt(28247)

dscw

r2scb <- ((1/28247)*15.5241)/(1+(1/28247)*15.4242)

r2scb

dscb<- (2*(3.94007))/sqrt(28247)

dscb

############## THREEWAY INTERACTION BG SEPARATE  ######################

#Black only

modelblack <- lme( RT ~ SalMax1n+cueing+cueing*SalMax1n, random=~1|NewS
ub, method= "ML", data=blackonly ) #method ML then anova works'
```

```
summary(modelblack)

dc6<- (2*(-1.02663))/sqrt(9976)

dc6

ds6<- (2*(-19.14913))/sqrt(9976)

ds6

dsc6<- (2*(4.61537))/sqrt(9976)

dsc6

#White only

modelwhite <- lme( RT ~ SalMax1n+cueing+cueing*SalMax1n, random=~1|NewS
ub, method= "ML", data=whiteonly ) #method ML then anova works'

summary(modelwhite)

dc7<- (2*(-16.135363))/sqrt(8867)

dc7

ds7<- (2*(-7.894251))/sqrt(8867)

ds7

dsc7<- (2*(-2.19526))/sqrt(8867)

dsc7

#Gray only

modelgray <-lme( RT ~ SalMax1n+cueing+cueing*SalMax1n, random=~1|NewSub
, method= "ML", data=grayonly ) #method ML then anova works'

summary(modelgray)

dc8<- (2*(-19.443621))/sqrt(9404)

dc8

ds8<- (2*(-8.34739))/sqrt(9404)

ds8

dsc8<- (2*(0.406451))/sqrt(9404)

dsc8
```

```
#####################################################################

################ Models 9 -20  UNCUED DATA, ONE FIXED FACTOR ##########

#Salience

modelnew9 <- lme( RT ~ SalMax1n, method= "ML",random=~1|NewSub, data=un
cuedonly ) #method ML then anova works'

summary(modelnew9)

#sal sig

dnew9<- (2*(-7.05036))/sqrt(14143)

dnew9

#Standard Deviation

modelnew10 <- lme( RT ~ Std1, method= "ML",random=~1|NewSub, data=uncue
donly ) #method ML then anova works'

summary(modelnew10)

dnew10<- (2*(0.18557))/sqrt(14143)

dnew10

#Overlap

modelnew11 <- lme( RT ~ OverlapRaw1, method= "ML",random=~1|NewSub, dat
a=uncuedonly ) #method ML then anova works'

summary(modelnew11)

dnew11<- (2*(-7.05036))/sqrt(14143)

dnew11

#PED

modelnew12 <- lme( RT ~ PEDn, method= "ML",random=~1|NewSub, data=uncue
donly ) #method ML then anova works'

summary(modelnew12)

dnew12<- (2*(-2.453129))/sqrt(14143)

dnew12

#BG PED
```

```
modelnew13 <- lme( RT ~ BGPEDn, method= "ML",random=~1|NewSub, data=unc
uedonly ) #method ML then anova works'

summary(modelnew13)

r.squaredGLMM(modelnew13

)

dnew13<- (2*(-6.64438))/sqrt(14143)

dnew13

#dcenter

modelnew14 <- lme( RT ~ dcenter, method= "ML",random=~1|NewSub, data=un
cuedonly ) #method ML then anova works'

summary(modelnew14)

#

dnew14<- (2*(-11.76892))/sqrt(14143)

dnew14

#d1

modelnew15 <- lme( RT ~ d1, method= "ML",random=~1|NewSub, data=uncuedo
nly ) #method ML then anova works'

summary(modelnew15)

#

dnew15<- (2*(-8.17958))/sqrt(14143)

dnew15

#d2

modelnew16 <- lme( RT ~ d2, method= "ML",random=~1|NewSub, data=uncuedo
nly ) #method ML then anova works'

summary(modelnew16)

#

dnew16<- (2*(-9.38532))/sqrt(14143)

dnew16
```

```
#d3

modelnew17 <- lme( RT ~ d3, method= "ML",random=~1|NewSub, data=uncuedo
nly ) #method ML then anova works'

summary(modelnew17)

#

dnew17<- (2*(-10.49892))/sqrt(14143)

dnew17

#d4

modelnew18 <- lme( RT ~ d4, method= "ML",random=~1|NewSub, data=uncuedo
nly ) #method ML then anova works'

summary(modelnew18)

#

dnew18<- (2*(-11.62269))/sqrt(14143)

dnew18

#d5

modelnew19 <- lme( RT ~ d5, method= "ML",random=~1|NewSub, data=uncuedo
nly ) #method ML then anova works'

summary(modelnew19)

#

dnew19<- (2*(-12.48802))/sqrt(14143)

dnew19

#d6

modelnew20 <- lme( RT ~ d6, method= "ML",random=~1|NewSub, data=uncuedo
nly ) #method ML then anova works'

summary(modelnew20)

#

dnew20<- (2*(-13.69479))/sqrt(14143)

dnew20
```

```
anova(modelnew9, modelnew10, modelnew11, modelnew12,modelnew13, modelne
w14, modelnew15, modelnew16,

      modelnew17, modelnew18, modelnew19, modelnew20)

########## MODELS 21-32 ONlY CUED DATA, ONE FIXED FACTOR  #############

modelnew17 <- lme( RT ~ SalMax1n, method= "ML",random=~1|NewSub, data=c
uedonly ) #method ML then anova works'

summary(modelnew17)

dnew17<- (2*(-8.57851))/sqrt(14017)

dnew17

modelnew18 <- lme( RT ~ Std1, method= "ML",random=~1|NewSub, data=cuedo
nly ) #method ML then anova works'

summary(modelnew18)

dnew18<- (2*(-0.764446))/sqrt(14017)

dnew18

modelnew19 <- lme( RT ~ OverlapRaw1, method= "ML",random=~1|NewSub, dat
a=cuedonly ) #method ML then anova works'

summary(modelnew19)

dnew19<- (2*(8.41919))/sqrt(14017)

dnew19

modelnew20 <- lme( RT ~ PEDn, method= "ML",random=~1|NewSub, data=cuedo
nly ) #method ML then anova works'

summary(modelnew20)

dnew20<- (2*(-13.59456))/sqrt(14017)

dnew20

modelnew21 <- lme( RT ~ BGPEDn, method= "ML",random=~1|NewSub, data=cue
donly ) #method ML then anova works'

summary(modelnew21)

dnew21<- (2*(-1.95999))/sqrt(14017)

dnew21
```

```
modelnew22 <- lme( RT ~ dcenter, method= "ML",random=~1|NewSub, data=cu
edonly ) #method ML then anova works'

summary(modelnew22)

dnew22<- (2*(2.61925))/sqrt(14017)

dnew22

modelnew23 <- lme( RT ~ d1, method= "ML",random=~1|NewSub, data=cuedonl
y ) #method ML then anova works'

summary(modelnew23)

dnew23<- (2*(-5.65702))/sqrt(14017)

dnew23

modelnew24 <- lme( RT ~ d2, method= "ML",random=~1|NewSub, data=cuedonl
y ) #method ML then anova works'

summary(modelnew24)

dnew24<- (2*(-3.70781))/sqrt(14017)

dnew24

modelnew25 <- lme( RT ~ d3, method= "ML",random=~1|NewSub, data=cuedonl
y ) #method ML then anova works'

summary(modelnew25)

dnew25<- (2*(-3.3113))/sqrt(14017)

dnew25

modelnew26 <- lme( RT ~ d4, method= "ML",random=~1|NewSub, data=cuedonl
y ) #method ML then anova works'

summary(modelnew26)

dnew26<- (2*(-3.05367))/sqrt(14017)

dnew26

modelnew27 <- lme( RT ~ d5, method= "ML",random=~1|NewSub, data=cuedonl
y ) #method ML then anova works'

summary(modelnew27)

dnew27<- (2*(-2.70603))/sqrt(14017)

dnew27
```

```
modelnew28 <- lme( RT ~ d6, method= "ML",random=~1|NewSub, data=cuedonl
y ) #method ML then anova works'

summary(modelnew28)

dnew28<- (2*(-2.35854))/sqrt(14017)

dnew28

anova(modelnew17, modelnew18, modelnew19, modelnew20, modelnew21, model
new22, modelnew23,

      modelnew24, modelnew25, modelnew26, modelnew27, modelnew28)


##### MODELS 32- 35, UNCUED DATA ONLY, MORE FIXED FACTORS #############

modelun32 <- lme( RT ~ SalMax1n+Std1+PEDn+BGPEDn+dcenter+d1+d2+d3+d4+d5
+d6, method= "ML",random=~1|NewSub, data=uncuedonly ) #method ML then a
nova works'

summary(modelun32)

dnew32s<- (2*(-2.610876))/sqrt(14017)

dnew32s

dnew32st<- (2*(-4.067206))/sqrt(14017)

dnew32st

dnew32ped<- (2*(0.225665))/sqrt(14017)

dnew32ped

dnew32pedbg<- (2*(1.883118))/sqrt(14017)

dnew32pedbg

dnew32dc<- (2*(-5.034372))/sqrt(14017)

dnew32dc

dnew32d1<- (2*(-2.940495))/sqrt(14017)

dnew32d1

dnew32d2<- (2*(-0.318156))/sqrt(14017)

dnew32d2
```

```
dnew32d3<- (2*(0.193725))/sqrt(14017)

dnew32d3

dnew32d4<- (2*(-0.335424))/sqrt(14017)

dnew32d4

dnew32d5<- (2*(0.928960))/sqrt(14017)

dnew32d5

dnew32d6<- (2*(-3.865563))/sqrt(14017)

dnew32d6

modelun33 <- lme( RT ~ SalMax1n+Std1+dcenter+d1+d6, method= "ML",random
=~1|NewSub, data=uncuedonly ) #method ML then anova works'

summary(modelun33)

anova(modelun32,modelun33)

dnew33s<- (2*(-2.406919))/sqrt(14017)

dnew33s

dnew33std<- (2*(-4.001235))/sqrt(14017)

dnew33std

dnew33dc<- (2*(-5.186381))/sqrt(14017)

dnew33dc

dnew33d1<- (2*(-3.687166))/sqrt(14017)

dnew33d1

dnew33d6<- (2*(-6.684414))/sqrt(14017)

dnew33d6

modelun34 <- lme( RT ~ Std1+dcenter+d1+d6, method= "ML",random=~1|NewSu
b, data=uncuedonly ) #method ML then anova works'

summary(modelun34)

r.squaredGLMM(modelun34)
```

```
dnew34std<- (2*(-7.870636))/sqrt(14017)

dnew34std

dnew34dc<- (2*(-5.412538))/sqrt(14017)

dnew34dc

dnew34d1<- (2*(-3.371773))/sqrt(14017)

dnew34d1

dnew34d6<- (2*(-6.682366))/sqrt(14017)

dnew34d6

#uncued black

modelun34black <- lme( RT ~ Std1+dcenter+d1+d6, method= "ML",random=~1|
NewSub, data=uncuedonlyblack ) #method ML then anova works'

summary(modelun34black)

r.squaredGLMM(modelun34black)

dnew34blackst<- (2*(-4.354207))/sqrt(5027)

dnew34blackst

#uncued white

modelun34w <- lme( RT ~ Std1+dcenter+d1+d6, method= "ML",random=~1|NewS
ub, data=uncuedonlywhite ) #method ML then anova works'

summary(modelun34w)

r.squaredGLMM(modelun34w)

#uncued gray

modelun34g <- lme( RT ~ Std1+dcenter+d1+d6, method= "ML",random=~1|NewS
ub, data=uncuedonlygray ) #method ML then anova works'

summary(modelun34g)

r.squaredGLMM(modelun34g)

anova(modelun33,modelun34,modelun32,modelun9, test="Chisq")

cor(uncuedonlyblack$Std1, uncuedonlyblack$Mean1)

cor(uncuedonlywhite$Std1, uncuedonlywhite$Mean1)

cor(uncuedonlygray$Std1, uncuedonlygray$Mean1)
```

```
cor(uncuedonlyblack$Std1, uncuedonlyblack$Skew1)

cor(uncuedonlywhite$Std1, uncuedonlywhite$Skew1)

cor(uncuedonlygray$Std1, uncuedonlygray$Skew1)

cor(uncuedonlyblack$Std1, uncuedonlyblack$EK1)

cor(uncuedonlywhite$Std1, uncuedonlywhite$EK1)

cor(uncuedonlygray$Std1, uncuedonlygray$EK1)

cor(uncuedonly$Std1, uncuedonly$Median1)

cor(uncuedonly$Std1, uncuedonly$Skew1)

cor(uncuedonly$Std1, uncuedonly$EK1)

cor(uncuedonly$Std1, uncuedonly$d1)

cor(uncuedonly$Std1, uncuedonly$dcenter)

cor(uncuedonly$Std1, uncuedonly$d6)

cor(dataset$Std1, dataset$Mean1)

cor(uncuedonly$Std1, uncuedonly$Median1)

cor(uncuedonly$Std1, uncuedonly$Skew1)

cor(uncuedonly$Std1, uncuedonly$EK1)

anova(modelun34,modelnew9,modelnew11)

anova(modelnew9, modelnew9a, modelnew9b, modelnew9c, modelnew9d, modeln
ew10, modelnew11, modelnew12,

      modelnew13, modelnew14, modelnew15, modelnew16, modelun33,modelun
34)

########### MODELS 36 - 38, CUED DATA ONLY, MORE FACTORS M ############

modelnew36 <- lme( RT ~ SalMax1n+PEDn+OverlapRaw1+dcenter+d1+d2+d3+d4+d
5+d6, method= "ML",random=~1|NewSub, data=cuedonly ) #method ML then an
ova works'

summary(modelnew36)

dnew36s<- (2*(-3.532179))/sqrt(14017)

dnew36s
```

```
dnew36ped<- (2*(-9.03551))/sqrt(14017)

dnew36ped

dnew36o<- (2*(2.104669))/sqrt(14017)

dnew36o

dnew36dc<- (2*(-4.758713))/sqrt(14017)

dnew36dc

dnew36d1<- (2*(-4.34617))/sqrt(14017)

dnew36d1

dnew36d2<- (2*(0.628166))/sqrt(14017)

dnew36d2

dnew36d3<- (2*(-0.271751))/sqrt(14017)

dnew36d3

dnew36d4<- (2*(-0.277762))/sqrt(14017)

dnew36d4

dnew36d5<- (2*(-0.170508))/sqrt(14017)

dnew36d5

dnew36d6<- (2*(-0.794145))/sqrt(14017)

dnew36d6

modelnew37 <- lme( RT ~ SalMax1n+PEDn+OverlapRaw1+dcenter+d1, method= "
ML",random=~1|NewSub, data=cuedonly ) #method ML then anova works'

summary(modelnew37)

dnew37s<- (2*(-3.529842))/sqrt(14017)

dnew37s

dnew37ped<- (2*(-9.028403))/sqrt(14017)

dnew37ped

dnew37o<- (2*(2.108285))/sqrt(14017)

dnew37o
```

```
dnew37dc<- (2*(5.059468))/sqrt(14017)

dnew37dc

dnew37d1 <- (2*(-6.627157))/sqrt(14017)

dnew37d1

modelnew38 <- lme( RT ~ SalMax1n+PEDn+dcenter+d1, method= "ML",random=~
1|NewSub, data=cuedonly ) #method ML then anova works'

summary(modelnew38)

r.squaredGLMM(modelnew38)

#black cued only

modelnew38black <- lme( RT ~ SalMax1n+PEDn+dcenter+d1, method= "ML",ran
dom=~1|NewSub, data=cuedonlyblack ) #method ML then anova works'

summary(modelnew38black)

r.squaredGLMM(modelnew38black)

dnew38blackped <- (2*(-6.324093))/sqrt(4911)

dnew38blackped

dnew38blackd1 <- (2*(--5.865705))/sqrt(4911)

dnew38blackd1

#white cued only

modelnew38w <- lme( RT ~ SalMax1n+PEDn+dcenter+d1, method= "ML",random=
~1|NewSub, data=cuedonlywhite ) #method ML then anova works'

summary(modelnew38w)

r.squaredGLMM(modelnew38w)

#gray cued only

modelnew38g <- lme( RT ~ SalMax1n+PEDn+dcenter+d1, method= "ML",random=
~1|NewSub, data=cuedonlygray ) #method ML then anova works'

summary(modelnew38g)

r.squaredGLMM(modelnew38g)
```

```
dnew38s <- (2*(-3.95429))/sqrt(14017)

dnew38s

dnew38ped <- (2*(-10.37862))/sqrt(14017)

dnew38ped

dnew38dc <- (2*(4.09543))/sqrt(14017)

dnew38dc

dnew38d1 <- (2*(-6.67561))/sqrt(14017)

dnew38d1

anova(modelnew17, modelnew18, modelnew19, modelnew20, modelnew21, model
new22, modelnew23,

      modelnew24, modelnew25, modelnew26, modelnew27, modelnew28,modeln
ew36,modelnew37,modelnew38)

anova(modelnew36,modelnew37,modelnew38)
```