Scan pattern adaptation during repeated visual search

by

Christopher Wayne Myers

A Thesis Submitted to the Graduate

Faculty of Rensselaer Polytechnic Institute

in Partial Fulfillment of the

Requirements for the degree of

DOCTOR OF PHILOSOPHY

Major Subject: Cognitive Science

Approved by the
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Rensselaer Polytechnic Institute
Troy, New York

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ABSTRACT

Sequences of eye movements, or scan patterns, can be repeated across multiple views of the same visual stimulus. Research on skill acquisition has demonstrated that participants implicitly refine sequential behavior with experience (Gray & Boehm-Davis, 2000; Haider & Frensch, 1999), and that the refinement process may lead to improvements when the structure of the task environment is supportive of improvements. The current research extends the understanding of scan patterns by demonstrating that they can be adapted to specific stimuli as experience with the stimuli increases. Functionally adaptive scanning theory is introduced as a theory of when and how scan patterns are adapted to repeating visual stimuli. FAST maintains that scan patterns repeat across the same stimulus during visual search and that scan patterns can be refined with increased use of the same scan pattern. FAST predicts that repeating scan patterns are refined to reduce time on task while maintaining accuracy. Three experiments were conducted to test FAST. The experiments demonstrate that although explicit strategies may be brought to a search task, they are implicitly refined.

1. Introduction & Historical Review

An ancient proverb attributed to Cicero (106-43 BCE) suggests that the eyes are the windows to the soul (Titelman, 1996). A more modern, less spiritual, assessment is that the eyes are the windows to the mind. Proponents of the eye-mind hypothesis assert that eye movements are intimately linked to cognition, such as memory, goals, and skills (Just & Carpenter, 1976). Consequently, understanding eye movement processes help to understand cognition.

Vision results from observer-environment interactions (Findlay & Gilchrist, 2003; O'Regan & Noe, 2001). On the observer side, eye movements are an integral part of the visual system. It is insufficient to restrict eye movements when studying vision. On the environment side, features of, and associations between, stimulus items within a visual environment also affect eye movement processes (Myers & Gray, submitted; Shen, Reingold, & Pomplun, 2000). Therefore, it is also insufficient to exclude how the environment affects eye movement processes.

The following work introduces a novel theory of visual scanning called functionally adaptive scanning theory (FAST). FAST is a theory of implicit changes to visual scans resulting from observer-environment interactions, which reflect implicitly acquired task-relevant scanning skills. FAST combines the functionality of visual scans (Laeng & Teodorescu, 2002; Noton & Stark, 1971a) with scanning theories and basic research on statistical influences on eye movements.

In this section, influences on eye movements and research on visual scans is presented, followed by details of FAST and its hypotheses. Finally, an introduction to the contextual cueing phenomena and its relation to FAST is provided.

1.1 Saccades and Scanning Patterns

Visual examinations can be broken into sequentially occurring instances where the eye is relatively stable (fixations/dwells) and when it moves at high velocities (saccades). Saccades carried out in succession result in scan patterns.

Studying saccades and scan patterns requires an active approach, as opposed to a passive approach, to vision research (Findlay & Gilchrist, 2003; O'Regan & Noe, 2001). The active vision approach advocates understanding vision through understanding saccades while the passive approach discounts saccades from explanations and theories of visual phenomena (Findlay & Gilchrist, 2003).

The passive approach is a category of experimental paradigms in which saccades are prevented during stimulus exposure (because of a brief exposure period) or in which saccades are allowed but not measured or considered as part of the explanation of visual phenomena. Because the passive approach has dominated much of the research in visual cognition, not much is known about visual scanning or its contribution to visual and perceptual phenomena.

The following sections first highlight influences on single saccades, then cover different types of scanning patterns. Next, scanpath theory, research on scanning patterns, and limitations of the research are presented.

1.1.1 Influences on Saccades

There are three reported influences that affect saccades: 1) *exogenous influences* (Everling & Fischer, 1998; Findlay, 1982, 1997; Franconeri & Simons, 2003; Franconeri, Simons, & Junge, 2004; Itti, Koch, & Niebur, 1998; Kowler, 1990; Mitchell, Macrae, & Gilchrist, 2002; Treisman & Gelade, 1980; Wolfe, 1994), 2) *endogenous influences* (Boot, McCarley, Kramer, & Peterson, 2004; Chernyak & Stark, 2001; Hayhoe & Ballard, 2005; Hayhoe, Shrivastava, Mruczek, & Pelz, 2003; Horowitz & Wolfe, 2001, 2003; Land & Lee, 1994; Land & McLeod, 2000; Peterson, Kramer, Wang, Irwin, & McCarley, 2001; Rayner, 1998; Yarbus, 1967), and 3) *statistical influences* (Chun, 2000; Chun & Jiang, 1998; Chun & Nakayama, 2000; Myers, 2004; Myers & Gray, submitted; Reder, Weber, Shang, & Vanyukov, 2003; Rosenholtz, 1999, 2001).

Exogenous influences (i.e., bottom-up, data-driven) refer to hypothesized interactions between environmental stimuli sufficiently distinct from surrounding areas (i.e., salient) and hardwired visual processes. For example, when a visual stimulus abruptly appears on a display it activates processes associated with attention, and triggers the process of shifting attention to the onset location. Although exogenous processes clearly require some level of cognitive processing (albeit at a relatively low level) they are typically thought of as reflexes facilitated by salient stimulus features.

Salient stimuli have been shown to attract attention and restrict the order of information visited (Franconeri, Simons, & Junge, 2004; Pomplun, Reingold, & Shen, 2003; Theeuwes, 2004; Wolfe, 1994). Consequently, exogenous influences are considered non-deliberate (Everling & Fischer, 1998; Findlay, 1982, 1997; Kowler, 1990; Mitchell et al., 2002), and can result in anarchic successions of individually programmed saccades (Wolfe, Alvarez, & Horowitz, 2000).

Endogenous influences (i.e., top-down, goal-driven) refer to deliberate influences on saccades, such as task goals like making a sandwich or batting a ball. Task goals affect the distribution of dwell locations and durations (Hayhoe, 2000; Hayhoe & Ballard, 2005; Hayhoe, Shrivastava, Mruczek, & Pelz, 2003; Land, Furneaux, & Gilchrist, 2002; Land & Lee, 1994; Land & McLeod, 2000; Land & Tatler, 2001).

Endogenous and exogenous influences do not represent a dichotomy, but rather opposite poles on a continuum. Located along the eye movement continuum are saccades that serve a goal, resemble a deliberate strategy yet are non-deliberate, and are acquired through statistical regularities within the environment. For example, when repeatedly searching through a visual environment (such as visual search), regularity within the visual environment (such as repeating distractor or target locations) can be used to improve task efficiency when the environmental regularities are associated with the goal. This type of saccade results from statistical influences. Visual attention mechanisms (Reder, Weber, Shang, & Vanyukov, 2003) and saccades (Myers & Gray, submitted) can be statistically influenced through experience with statistical patterns of task-relevant information (see Figure 1).

It could be argued that what has come to be known as exogenous influences result from an interaction between inexperience with a task *and* salience within the task environment. For example, Rosenholtz (1999; , 2001) argues that statistical differences between stimulus features within a certain spatial proximity *is* visual salience–salient areas are statistical outliers across different stimulus features within an area. These statistical outliers capture attention when they are not mediated in some way, such as experience with the environment. Likewise, it could also be argued that endogenous processes are statistically influenced saccades that have changed from an implicit process to an explicit, goal-directed strategy through their experienced benefit (Siegler &

Stern, 1998; Sun, Merrill, & Peterson, 2001). Consequently, the eye movement continuum more generally reflects the degree to which statistical properties of the task environment influence saccades (see Figure 1).

To briefly summarize, there are three saccadic influences typically reported–endogenous, exogenous, and statistical. These labels add to confusion because both endogenous and exogenous influences reflect statistical influences. Because visual scanning patterns are temporally consecutive saccades, they too are influenced by the statistical structure of the task environment. The following section covers differences between different categories of visual scans. Next, scanpath theory is presented as a theory of repeating scan patterns. Further research on scanning patterns is then provided. The section ends with limitations of research on scanning patterns.

1.1.2 Different Types of Visual Scans

There is ambiguity in the terms used to describe visual scans. Many researchers create the ambiguity by using terms like "scanpath," "visual scan," "scan path," and "scan pattern" interchangeably to describe successions of saccades. To reduce ambiguity, the term *visual scan* will be used as a general term and does not connote any particular underlying process or repeatability–it simply defines a succession of saccades. The term *repeating scan patterns* will be used to label highly similar visual scans, and does not imply that a single influence (endogenous or exogenous) leads to the high degree of similarity between the scans. The term *scanpath* is reserved for repeating scan patterns hypothesized to result from only endogenous influences (Chernyak & Stark, 2001; Grosbras et al., 2001; Josephson & Holmes, 2002; Noton & Stark, 1971a, 1971b; Pieters, Rosbergen, & Wedel, 1999; Stark & Ellis, 1981; Stark et al., 1980; Zangemeister, Sherman, & Stark, 1995) (see Figure 1).

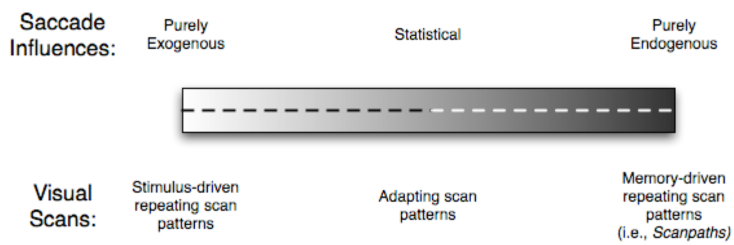

Figure 1. Continuum representing the relationship between stimulus-driven repeating scan patterns, adapting scan patterns and memory-driven repeating scan patterns (i.e., scanpaths).

Differentiating between stimulus-driven repeating scan patterns, adapting scan patterns, and scanpaths is important for hypothesizing the underlying influences on visual scans. If either memory-driven or stimulus-driven repeating scan patterns are present in the behavioral data, then they can be linked to either purely endogenous or purely exogenous processes, respectively. Determining when a visual scan is a stimulus-driven repeating scan pattern or a scanpath can be difficult, and will be covered in a following section. Moreover, if adapting scan patterns are present in the behavioral data, then they can be related to a mixture of exogenous and endogenous processes. Because the scan patterns are adapting with experience, their adaptation is hypothesized to be governed by processes associated with skill acquisition, such as proceduralization and automaticity (Blessing & Anderson, 1996; Haider & Frensch, 1999). The following sections will cover research on scanpath theory and scan patterns.

1.1.3 Scanpath Theory

Noton and Stark (1971a; , 1971b) reported that visual scans produced while freely viewing a scene are stored in memory and are specific to individuals and the scene presented. The scans can then be repeated across the same stimulus by recalling the scanning information from memory, and the term scanpaths was coined for these types of visual scans. Noton and Stark interpreted scanpaths as revealing something about how humans perceive and process visual patterns in the environment. Over a twenty-year period, the authors developed a theory of scanpath construction and execution. Two hypotheses central to the scanpath theory are (1) that perception involves saccades, and (2) that the encoding, storage, and retrieval from memory of saccades across the stimulus are integral to recognizing previously viewed stimuli. The basic assumption is that visual perception is a pattern-learning process where an internal representation of a viewed stimulus is stored as a pattern in memory and that recognizing a stimulus is the process of retrieving the stored pattern from memory. According to scanpath theory, scanpaths are the patterns stored in memory.

Noton and Stark (1971a; , 1971b) distinguish between a *learning phase* and a *recognition phase* for image recognition. During the learning phase, a visual scan occurs while freely viewing a stimulus, and is stored in memory. During the recognition phase, the same scan pattern is retrieved from memory and instantiated when the same stimulus is subsequently presented. The authors interpret the repeated scan pattern during the subsequent stimulus presentation as an instance of recognizing the stimulus; however, the authors did not hypothesize how scan patterns were stored in, or retrieved from, memory. Based on Noton and Stark's theory, their repeating scan patterns can be classified as scanpaths. Indeed, it was Noton and Stark who coined the term scanpath to describe repeating scan patterns as occurring from sequences of saccades stored in memory. However, there is a chicken-and-egg problem with Noton and Stark's explanation of repeating scan patterns: it is unclear if recalling the stimulus resulted in the repeated scan pattern, or if repeating scan patterns lead to recalling the stimulus.

Noton and Stark liken memorizing and recalling scanpaths to memorizing and recalling "a conventional sequence of behavior" (1971b, pp. 936-937), such as executing a solution to a Tower of Hanoi puzzle that is retrieved from memory (Simon, 1999). The authors also report that scanpaths are similar within participants and different between participants.

1.1.4 Research on Scanning Patterns

Since Noton and Stark's initial reports (1971a; , 1971b), evidence has continued to be reported on the nature of scanpaths and repeating scan patterns. Stark and Ellis (1981) studied eye movements of participants repeatedly viewing perceptually dynamic images such as ambiguous figure illusions (see Figure 2).

Figure 2. Ambiguous figure illusion. The image can be perceived as a young woman turning her head, or as an older woman in a shawl.

Stark and Ellis (1981, p. 214) found evidence that scans change considerably with different cognitive states (different perceptions of the ambiguous stimulus) and interpret this as indicative of "cognitive models," or stored saccade programs hypothesized to occur in scanpaths. Again there is a "chicken-and-egg" problem here: it is difficult to determine from their report if the shifts in perception changed the scanning pattern, or if changes in the scanning pattern changed the perception of the ambiguous image.

Further evidence that repeating scan patterns are stored as cognitive models, predicted by scanpath theory, is provided by Brandt, Stark, Hacisalihzade, Allen, and Tharp (1989). The authors questioned whether internalized visual images (i.e., imagined scenes) are scanned in the same way as during a physical presentation of the same scene. The authors used two irregularly checkered matrices as their stimuli; half of the participants saw one stimulus and the other half saw the second stimulus. Brandt et al. conclude that scanning patterns from a viewed stimulus "reflect" scanning patterns of an imagined stimulus.

Laeng and Teodorescu (2002) replicated the findings of Brandt et al. (1989), and concluded that repeating scan patterns play a functional role rather than an epiphenomenal role during visual imagery, further supporting scanpath theory. In two experiments, participants viewed an irregular checkerboard or color pictures of fish and were subsequently asked to form mental images of these stimuli while keeping their eyes open.

During a "perceptual phase," a group of participants was requested to maintain fixation at the screen's center, whereas another group was free to inspect the stimuli.

During an "imagery phase", all of the participants were free to move their eyes. In Experiment 2, a third group of participants was free to explore the pattern during the perceptual phase but was required to maintain central fixation during the imagery phase.

For participants free to explore the pattern, the percentage of time spent fixating a specific location during perception was significantly correlated with the time spent on the same locations during imagery. The scanning order during the imagery phase was correlated to the order during the perceptual phase. Importantly, the strength of relatedness between scan patterns predicted performance accuracy. Participants who fixed their gaze centrally during the perceptual phase did the same spontaneously during the imagery phase, even though they were free to move their eyes. Participants free to explore during the perceptual phase, but maintaining central fixation during the imagery phase, showed decreased ability to recall the pattern. Laeng and Teodorescu (2002) conclude that efferent commands to the eye and proprioceptive information while initially scanning a stimulus are stored with the encoding of each eye dwell during perception, and are later used during the regeneration of the imagined stimulus as an index to the location of a part of the image.

Pieters, Rosbergen, and Wedel (1999) examined if Noton and Stark's scanpath theory could inform marketers on the wear-out speed of printed advertisements over repeated exposure. The authors found that repeating scan patterns obey a stationary, reversible, first-order Markov chain and remain constant across repeated exposure to printed advertisements. Pieters et al. (1999) also reported that attention duration decreases significantly across repeated exposures to the printed advertisements.

Finally, Josephson and Holmes (2002) tested the robustness of scanpath theory in the domain of the World Wide Web. The authors compared scan patterns collected from participants while viewing web pages, and concluded that their results generally support scanpath theory. However, the authors found that some visual scans were similar between participants, contrary to scanpath theory.

Using functional magnetic resonance imaging, Grosbras, Leonards, Lobel, Poline, LeBihan, and Berthoz (2001) studied the dependence of repeating scan patterns on different types of memory by analyzing cortical activity during performance of novel and well learned scan patterns. The results indicate that novel scan patterns require specific cortical resources related to effortful sequence preparation and coordination as well as resources associated with spatial working memory. For learned scan patterns, similar cortical areas received reduced activation. Furthermore, areas associated with memory were recruited (e.g., parahipocampal area) during the execution of learned scan patterns. The authors conclude that neural resources recruited by the visual system can change with the familiarity of the scan pattern. This study provides evidence that well learned scanning patterns are cortically distinct from novel patterns.

Gilchrist and Harvey (in press) present evidence that scanning behavior in visual search includes a systematic component. Participants' task was to search for a target that was either present or absent within grid-like displays. Participants searched through many trials, and all spatial configurations for each trial were distinct. Participants generated more horizontal saccades than vertical saccades while searching for the target. Disruption of the grid structure in the display moderated but did not eliminate the systematic component. The authors note that this is consistent with scanpath theory. Although the authors found evidence of systematic components during visual search, they did not present evidence that scan patterns repeated across searches. Rather, the authors demonstrate that participants preferred horizontal saccades to vertical saccades. Although this arguably results from endogenous influences, it does not demonstrate that scan patterns are repeatedly used during their visual search task.

Gilchrist and Harvey's results demonstrate an important point regarding repeated scan patterns–the task environment must be structured such that repeating the same scan pattern is: 1) possible, and 2) potentially useful, otherwise there is no reason to store and repeat scan patterns as suggest in scanpath theory. The visual task environment must be relatively stable across multiple views to acquire and repeat scan patterns during visual search tasks.

In summary, there is empirical evidence that repeating scan patterns are scanpaths, and thus cognitively imposed as originally hypothesized in Noton and Stark's scanpath theory (1971a; , 1971b). Though contrary to Noton's and Stark's original proposition, there is evidence that scan patterns are similar across individuals (Josephson & Holmes, 2002). Similarity across individuals could result from the completing the same goal in the same stimulus or from pure exogenous influences. Noton and Stark also theorized that scan patterns are acquired during the initial view of a stimulus, stored as "cognitive models," and repeated during subsequent views of the same stimulus. The same "model" is retrieved whether the review is imaginary or physically present. To acquire, store, retrieve, and use a scan pattern on a stimulus, components of the stimulus must be unchanged across multiple views. The paradigm used in all reported research uses unchanging stimuli across repeated views; consequently, repeating scan patterns have been regularly found. Furthermore, there is empirical evidence that separate cortical areas are active when learned scan patterns are executed when compared to novel patterns. Finally, repeating scan patterns are hypothesized to present a more computationally economic approach to scheduling eye movement sequences when compared to novel sequences.

1.1.5 Potential Limitations of Scanning Research

Although there is much empirical evidence for repeating scan patterns and scanpath theory, there are three potential limitations to all of the reviewed research. First, a slight majority of the reviewed research came from a single laboratory. Second, all of the reviewed research used a free-view paradigm (excluding Grosbras et al., 2001). Third, there is difficulty in detecting statistically significant differences between stable visual scans.

Replication is a crucial component of any empirical result. The ability to replicate a result bolsters confidence that the result is understood and reproducible. Ideally, replication should occur both within, and outside of, the lab where the result originated. Of the nine reported scanning results reviewed in previous sections (excluding Gilchrist & Harvey, in press), a slight majority (5) of the reported scanning research came out of Dr. Lawrence Stark's laboratory. Even so, repeating scan patterns have been successfully replicated in other labs (Grosbras et al., 2001; Josephson & Holmes, 2002; Laeng & Teodorescu, 2002; Pieters, Rosbergen, & Wedel, 1999). For behaviors thought to be as dissimilar and chaotic as scan patterns (Wolfe, Alvarez, & Horowitz, 2000), this replication record is very strong. Unfortunately, it is difficult to determine the number of failed attempts at replication, as most journals do not publish null empirical results. It can be construed that not enough replication has been done outside of Stark's laboratory to adequately evaluate the reproducibility of repeating scan patterns, but this is more an argument to continue research then one diminishing scanpath theory and the phenomenon.

The second limitation is that scanning research conducted inside and outside Stark's laboratory has only used a free-view paradigm (excluding Grosbras et al., 2001). The free-view paradigm consists of displaying an image to participants and simply instructing them to 'remember the image.' This is an important limitation on scanpath theory because it is difficult to generalize to different environments when only studying a phenomenon within a single paradigm.

Earlier, the point was made that regularity within the visual environment is important when studying and understanding scan patterns. Indeed, the free-view paradigm provides such regularity by having participants repeatedly view the same image. However, repeating scan patterns may also occur in tasks other than free-view, such as visual search tasks where the visuospatial arrangement of searched through items is identical across multiple views, providing regularity. Regularity within visual search tasks highlights a potential research paradigm to study visual scans. Traditional visual search tasks rarely repeat the same visuospatial arrangement of items to be searched through, reducing the ability for participants to adapt to regularity within the task environment. However, when repeated spatial layouts of items are searched through and paired with a constant target location, participants exploit this pairing and reduce the times of their searches (Chun, 2000; Chun & Jiang, 1998).

The use of a goal-directed task, such as visual search with regularity, reduces the difficulty associated with statistical analyses on visual scans when compared to the free-view paradigm. The free-view paradigm makes it relatively difficult to (a) easily determine the beginning and ending of a visual scan, (b) determine which scans should be compared, (c) hypothesize differences between scans, and (d) hypothesize why scans may change over time. With goal-direct tasks, (a) the beginning and ending of a visual scan could be the beginning and ending of a visual search trial, (b) scans from within- and between-participant search conditions should be compared appropriately (not all scans compared against all other scans), (c) scans may be hypothesized to change differentially based on within- and between-participant manipulations on stimuli, and (d) changes in scans can be hypothesized if and when regularity is systematically introduced into the task environment.

Finally, the third limitation of scanning research is the ability to compare scan patterns. As the research moved outside of Stark's laboratory, new comparison methods were developed. For instance, Laeng and Teodorescu (2002) used statistical regression analyses to determine if the initial view of a stimulus predicted the scanning order when imagining the same stimulus. The authors regressed the serial order of the first 9 items fixated during the initial view of a stimulus on the first 9 items fixated while imagining the initially viewed stimulus, and were able to obtain statistically significant positive linear relationships.

Pieters et al. (1999) used probability estimates of scanning behavior derived through Markov processes. Abbot and Hrycak (1990) touched on several limitations to Markov process models. The authors argued that testing of the Markov process model, in terms of resemblance between modeled scan patterns and those produced by participants, (1) requires a technique for assessing similarity between the patterns, (2) categorizing patterns, and (3) identifying typical patterns. Abbott and Hrycack argued that Levenshtein distances provide all three, and provide an opportunity to employ clustering analytics to determine families of similar behavioral sequences. The Levenshtein distance, or minimum-edit distance, between two strings (or visual scan patterns) is given by the minimum number of operations needed to transform one pattern into the other, where an operation is an insertion, deletion, or substitution of a single dwell (Levenshtein, 1966).

Josephson & Holmes (2002) computed Levenshtein distances to objectively determine the similarity between multiple scan patterns. However, Josephson and Holmes (2002, p. 547) characterize this approach as "…descriptive and interpretive in nature." resulting from the their lack of statistical significance tests applied to the Levenshtein distances.

Each of the three approaches provide objective comparisons between visual scans and demonstrate a shift toward increased measurement rigor from when visual scan similarities were determined by 'eyeballing' data (Yarbus, 1967). Josephson and Holmes (2002) suggest an approach for determining statistical differences between visual scans.

Furthermore, of the three methods, Levenshtein distances afford techniques that the others do not, such as the ability to quantify the similarity between two scan patterns.

1.1.6 Summary

Visual scans may repeat across multiple views of the same stimulus, resulting from purely endogenous influences (scanpaths) or from purely exogenous influences (stimulus-driven repeating scan patterns). Furthermore, visual scans can adapt to the statistical structure of the task environment (adapting scan patterns) and can become proceduralized and automated prior to adaptation (see Figure 1).

There is clear evidence that repeating scan patterns have been observed across many empirical studies using a free-view paradigm. Stark and colleagues (Noton & Stark, 1971a, 1971b; Stark & Ellis, 1981; Stark et al., 1980) hypothesize that repeating scan patterns are scanpaths, and are thus stored as “cognitive models” in long-term memory after an initial view of a stimulus. The “models” are recalled when subsequently viewing the same stimulus. Repeating scan patterns have been compared using a number of methods from eye-balling the data (Yarbus, 1967) to the use of Levenshstein distances (Josephson & Holmes, 2002).

There are three limitations of the reviewed scanning research. First, visual scans have only been acquired and compared from free-view paradigms. Other paradigms (e.g., visual search and contextual cueing) must be used to adequately determine the prevalence of repeating scan patterns. The second limitation results from the first: only descriptive statistics have been used to determine trends in scan patterns (i.e., clustering analytics). The second limitation can be overcome by using a paradigm that has a clear and explicit goal (e.g., finding a target among distracters) where hypotheses become clearer than in a free-view paradigm and allow for the use of inferential statistics (i.e., analysis of variance). The third limitation of the reviewed research is minor–a majority of the reported results have come from a single laboratory. This limitation is not fatal, and suggests that further work outside of the originating laboratory is needed.

If repeating scan patterns are indeed scanpaths as asserted by Noton and Stark, then scanpaths should be affected by processes associated with skill acquisition, such as proceduralization and automaticity. Moreover, scanpaths should change with increased use to reduce the amount of viewed information necessary for completing the goal across repeated scans of the same stimulus. The following section introduces functionally adaptive scanning theory, as a theory of repeating and changing scan patterns.

1.2 Functionally Adaptive Scanning Theory (FAST)

There is evidence that similar scan patterns occur on repeated visual stimuli and contain several attributes. For example, similar scan patterns are 1) mostly idiosyncratic (Noton & Stark, 1971a, 1971b; Pieters, Rosbergen, & Wedel, 1999; Stark & Ellis, 1981; Stark et al., 1980; Zangemeister, Sherman, & Stark, 1995) but 2) can be similar between participants (Josephson & Holmes, 2002), 3) are important to visual imagery (Brandt, Stark, Hacisalihzade, Allen, & Tharp, 1989; Laeng & Teodorescu, 2002), and 4) have been correlated to neural structures that differ to the neural structures involved in novel scan patterns (Grosbras et al., 2001). Functionally adaptive scanning is a theory (FAST) that incorporates the research community's understanding of statistical influences on saccades and scan patterns to understand changes in repeating scan patterns. The current section provides an overview of FAST and its hypotheses.

1.2.1 FAST Overview

> "The demands that the functional task environment makes on human cognitive, perceptual, and action operations causes these operations to adapt to each other and to the functional task environment…Sometimes these adaptations result in a readjustment that is limited to cognition, perception, and action; other times these adaptations result in changes in the pattern of use of mental versus environmental resources; and sometimes an operator's actions adapt the environment itself which then may lead to additional adaptations and changes." Gray, Neth, and Schoelles (in press).

This statement of human-environment interactions and adaptations succinctly captures the theoretical position and approach behind FAST. Functionally adaptive scanning is a theory of human visual scanning that integrates the phenomena of repeating scan patterns with influences from statistical regularities within a task environment. Scanning patterns, and eye data in general, reflect adaptations to statistical regularities of features in a task environment. The more constant the features, the greater the behavioral adaptation expected, up to some unknown limit. The central tenets of FAST follow from this and are (1) visual scans are functional, contributing to goal completion in ways other than simply orienting the eyes to acquire information, such as aiding in the recall of stored information from a previously scanned scene (Laeng and Teodorescu, 2002); and (2) visual scans are potentially adaptive, such that repeating scan patterns can be refined over time, increasing task efficiency while simultaneously reducing scanning times. Consequently, changes in scan patterns can be interpreted as refinement. When the refined scan patterns result in decreased times to recognize a stimulus or to respond to questions regarding a stimulus while maintaining response accuracy, then refinement can be considered beneficial. Beneficial behavioral refinement is a typical determinant of skill acquisition, and will be referred to as the *behavior-refinement hypothesis*, which is an extension of Haider & Frensch's information-reduction hypothesis (1999).

FAST is rooted in the active vision research approach, and incorporates the behavior-refinement hypothesis with repeating scan patterns. FAST makes 3 propositions: 1) that repeating scan patterns form in stable visual environments, 2) goal information (e.g., the location of a target during a visual search task) can become associated with repeating scan patterns, and 3) repeating scan patterns paired with goal information can be refined to a smaller and smaller number of behaviors (e.g., saccades), functionally adapting repeating scan patterns to a goal associated with a task environment, effectively reducing time-on-task while sustaining accuracy. There are three criteria that must be present to conclude that repeating scan patterns were refined. The three criteria are:

Criterion-1. participants should reduce the number of eye fixations necessary to find the target across search trials;

Criterion-2. visual scans should become increasingly similar across repeated searches through the same stimulus independent of the number of saccades composing the visual scans;

Criterion-3. scan patterns from identical and repeating stimuli will become more similar at a faster rate than scan patterns from novel stimuli.

All three criteria must be met to conclude that visual scans are refined across repeated searches through the same stimulus.

The three criteria should be manifested in two types of observable eye movement behavior. First, eye fixations can be analyzed for changes as a function of task experience, and is the focus of criterion 1. Second, scan pattern similarities can change as a function of task environment regularity and experience, and is the focus of criteria 2 and 3.

For example, over the course of repeatedly searching through the same visual stimulus display and finding the associated target, scan patterns would first repeat, then become paired with goal information, and then refined. It is important to note that these are not discrete stages, one occurring before the other, and in fact the number of dwells to find a target can be reduced while visual scans become increasingly similar. FAST also assumes that refinement is an implicit process, and is based on the finding that search displays are implicitly learned across repeated searches through the same search display (Chun, 2000; Chun & Jiang, 1998; Chun & Nakayama, 2000).

1.2.2 Three Possible Influences on Predicted Refinement in FAST

Exogenous and endogenous influences can be considered as two extremes of statistical influences on goal-oriented behavior. Between these extremes are non-deliberate behaviors that serve a goal and appear strategic. The two extremes and the area between them are useful for predictions of scanning refinement (see Figure 1).

Scans that result from purely endogenous influences would not be refined because the same endogenous scan pattern would be repeatedly used. For example, after completing a goal by scanning a stimulus for the first time, all subsequent scan patterns in service of the same goal on the same stimulus would be nearly identical to the first scan pattern. Although this seems very unlikely and a “straw man” influence, this is precisely what is predicted by scanpath theory (Noton & Stark, 1971a, 1971b). Indeed, it is certainly the case that competing endogenous strategies could alternate. For example, a counterclockwise versus clockwise search pattern could be instantiated, and both would be in service of the same goal. However, alternating between two, or more, endogenous strategies would result in a few repeating scan patterns, but not to scan pattern refinement.

Behavior from purely exogenous influences would not be refined, either. The same stimulus would always influence scan patterns in the same manner, leading to repeating scan patterns. It is unknown if exogenous influences differ across individuals. If exogenous influences are assumed to be similar to reflexes (and therefore likely to be similar across individuals), then repeating scan patterns on the same stimulus should be very similar across individuals. (Note that this does not imply that scan patterns will be identical, but only very similar as there is likely noise in the visual system keeping scan patterns from being consistently exact.) However, if exogenous influences differ between individuals, then repeating scan patterns would likely differ between individuals.

The extreme influences are clearly difficult to distinguish with observable behavior. Indeed, it is unlikely that either extreme influence (endogenous or exogenous) is ever in sole command of behavior. Rather, it is more likely that behavior results from influences falling somewhere between these extremes. Learning is assumed to be absent in both extremes. Endogenous influences may occur after learning had ceased such as a settled on and deliberate strategy, while purely exogenous influences are by definition void of learning. Although it would be difficult to differentiate between endogenous and exogenous influences, it is possible to detect differences between statistical and endogenous influences, and statistical and exogenous influences. This is because effects of statistical influences are useful to the processes associated with learning and adaptation (Blessing & Anderson, 1996; Gray, Sims, Fu, & Schoelles, 2006; Haider & Frensch, 1999). As experience with a task environment and a paired goal increase, influences may shift from what appear to be exogenous influences to what appear to be to be endogenous influences, though may never become a deliberate or consciously executed strategy.

1.2.3 Summary

FAST incorporates the phenomena of repeating scan patterns with the behavior-refinement hypothesis into a single theory of visual scanning. FAST maintains that visual scans are functional and can be adapted through a behavior-refinement process. For refinement to occur, the task environment must support it through statistical regularity between the stimulus and the task goal, and the stimulus-goal pair must occur repeatedly. To claim evidence for FAST, three criteria must be met: (1) participants must reduce the number of saccades necessary to complete a goal with increased experience, (2) visual scans must become increasingly similar across repeated searches through the same stimulus independent of the number of saccades comprising scans, and (3) scanning patterns from viewing repeating stimuli must become more similar at a faster rate than novel stimuli.

To provide evidence for FAST, a paradigm that satisfies 3 important criteria must be adopted. First, the paradigm must contain multiple repeating stimuli across several trials. Second, each stimulus must be independent and associated with a specific goal (e.g., visual search). Third, the paradigm must use adequate controls with which to compare visual scans from repeating stimuli, such as multiple unique stimuli. The contextual cueing paradigm satisfies all three criteria (Chun & Jiang, 1998). Contextual cueing is a phenomenon that produces shorter reaction times when finding a target in repeating stimuli than in unique stimuli, and has been shown to result from implicit processes. Interestingly, the contextual cueing phenomena can be simply explained as a by-product of FAST, and no special hypotheses are needed. Furthermore, the FAST explanation of contextual cueing differs from the accepted account. In the next section, the contextual cueing paradigm will be introduced along with important aspects of the contextual cueing phenomenon, as well as the accepted theory of the cueing process.

1.3 Contextual Cueing

When visual contexts are repeatedly viewed in the service of the same goal, the goal is completed at an increasingly faster rate than the same goal in novel contexts (Chun, 2000; Chun & Jiang, 1998; Song & Jiang, 2005). For example, repeatedly viewed visuospatial configurations of items on a display, or *contexts*, can reduce the time to find a target (goal) across repeated searches through the same contexts. Chun, Jiang, and others show that repeatedly viewed contexts guide spatial attention to the target location during visual search (Chun, 2000; Chun & Jiang, 1998; Jiang & Wagner, 2004; Song & Jiang, 2005), and that paired associations between a context and the associated target location occur implicitly. This effect is referred to as *contextual cueing*.

Contextual cueing is an implicit adaptation to functional relationships within the task environment (Chun & Jiang, 1998), resulting in the minimization of cost, in units of time, at the task level (Gray, Sims, Fu, & Schoelles, 2006; Myers & Gray, submitted). Although contextual cueing has been documented and its underlying processes alluded to in many studies (Chun, 2000; Chun & Jiang, 1998; Jiang & Wagner, 2004; Lleras & Von Muhlenen, 2004; Peterson & Kramer, 2001; Song & Jiang, 2005), a process account involving saccades remains absent from explanations of cueing effects. The current section introduces the typical contextual cueing paradigm, provides an overview of essential results, and relates the paradigm and phenomenon back to FAST.

1.3.1 Contextual Cueing Paradigm

The contextual cueing paradigm is a visual search task with very similar targets and distracters, making search serial and inefficient. Similar target and distractor types reduce "any attentional capacity to perform explicit cognitive operations other than search," (Chun & Jiang, 1998, p. 33). Participants search for a target within repeating and unique contexts, and the target is present on every trial. Context is operationally defined as the visuospatial arrangement of target and distractor items.

Participants are presented with a context, and their goal is to find the target. Once the target is found, participants respond to a particular feature of the target, such as its orientation.

Targets in repeating contexts are always presented at the same location, but the target feature associated with the correct response may change. For example, the first time you see repeating context *A* the target may be oriented so that the correct response is "right". The next time you see repeating context *A* the target will be in the same location, but could be oriented so that the correct response is now "left". Consequently, target location is cued by the context, rather than the response (e.g., right or left). Unique contexts are not predictive of the target location, providing a control. Each experiment presents many trials from which only a very small set (≈ 3% of all trials) are repeating contexts.

Response times have been the only dependent variable reported in contextual cueing experiments. Results regularly demonstrate reduced response times for both repeating and unique contexts over blocks of trials. However, response times from repeating contexts become increasingly faster than response times from unique contexts, and this difference is the contextual cueing effect (see Figure 3).

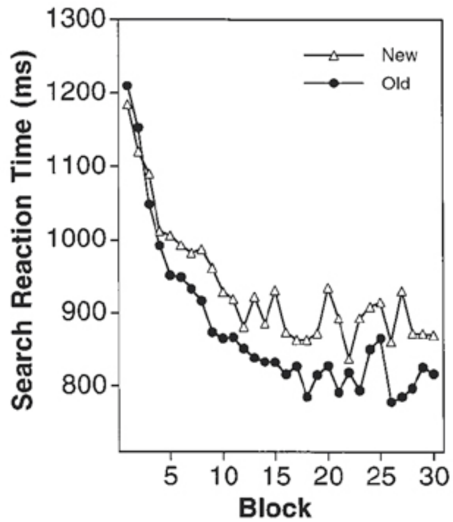

Figure 3. Contextual cueing effect. Search reaction time (ms) for repeating contexts (old) improve beyond unique contexts (new) by the end of the 5th block (Figure 2 from Chun & Jiang, 1998, p. 38).

It is important to report how unique and repeating contexts are typically created. The frequency with which a target may appear in a given location is equated for both repeated and unique context. The following steps provide a walkthrough of the process. First, an even number of different target locations is determined. Half of the target locations are for unique contexts, and half are for repeating contexts. Distractor locations are then added to target locations for repeating contexts, under the condition that the added distractor locations do not come within a specified minimum item-to-item distance. Once this is done, the same repeating contexts are used across the experiment. Consequently, when it is time to display one of the repeating contexts, a repeating context is randomly selected without replacement from the set of repeating contexts and displayed to the participant.

When it is time to display one of the unique contexts, one of the target locations set aside for unique contexts is randomly selected without replacement. Distractor locations are then added to the target location to create a unique context, under the condition that the items (distractors and targets) do not come within the specified minimum item-to-item distance.

Once the sets of unique context target locations and repeating contexts have been exhausted, a new block of trials begins with the same unique context target locations and the same repeating contexts. Consequently, unique contexts are not completely unique, as target locations repeat from block to block. The repetition of unique context target locations across blocks was implemented to control for learning of a relatively small number of target locations necessary for repeating contexts. If a contextual cueing effect had occurred without controlling for the learning of target locations, it would be impossible to conclude that the repeating spatial configurations were leading to the speed up in response times.

1.3.2 Overview of Results from Contextual Cueing Experiments

Searches through repeating contexts improve search times beyond those from unique contexts. Improvements are hypothesized to result from the cueing of target locations from repeating contexts. Furthermore, it is hypothesized that memory for visual context is instance based and implicitly learned over repeated exposure to the same context. This section highlights essential results from the contextual cueing literature.

Chun and Jiang (1998) conducted a series of experiments that introduced the contextual cueing effect. The authors found that changes to the item features at distractor and target locations across trials of repeating contexts (e.g., locations originally containing a ‘3’ changed to contain ‘B’) did not hinder cueing (Chun & Jiang, 1998, experiment 3), demonstrating cueing results from the spatial arrangement of locations rather than the information at each location. Repeating contexts reliably cued target location during a speeded response phase consisting of briefly presented stimuli (200 ms). The phase occurred after contextual cueing was established during a long training period (Chun & Jiang, 1998, experiment 5). Finally, contextual cueing effects remained robust in the face of random distractor and target location jitter, and when two target locations were paired with the same repeating context (Chun & Jiang, 1998, experiment 6), demonstrating that minor contextual noise does not impede cueing.

Chun & Jiang (1998, experiment 5) attempted to rule out scan patterns as the contextual cueing mechanism. Participants completed a 3-phase task. During the training phase, participants were instructed to find a rotated target (T) among rotated distractors (L) and respond to the target's direction (right or left). This phase continued for 20 blocks of trials. Within a block, all stimulus configurations (i.e., contexts) were unique, however, across blocks, 12 configurations repeated. Thus, participants viewed 12 repeating contexts 20 times each, and 240 unique contexts once each.

Three displays composed a single trial during the training phase: a dwell control display, a stimulus display, and a feedback display. Participants were instructed to fixate a small dot on the dwell control display until the stimulus display was presented (≈ 500 ms). The stimulus display remained visible until a response was given. After the response, a blank screen was displayed and accuracy feedback was provided. The feedback display remained for 1,000 ms and was then replaced by a dwell control display signaling a new trial. Chun and Jiang (1998) report that participants demonstrated a cueing effect by the end of the training phase.

After completing the training phase, participants completed a testing-practice phase and testing phase. During the testing-practice and testing phases, four displays composed a single trial. Each trial began with a dwell control display that remained visible for 600 ms followed by the stimulus. The stimulus display was presented for 200 ms. After 200 ms, the stimulus was replaced with a blank screen that remained present until the participant responded with the rotation of the target. Following a response, accuracy feedback was presented with tones signaling either correct or incorrect responses. After 1000 ms, the dwell control display reappeared signaling a new trial. In the testing-practice phase, participants completed 2 blocks of unique context trials (24 total trials). In the testing phase, participants completed 10 blocks of unique and repeating context trials. The key comparison of the testing phase was the accuracy levels between repeating and unique contexts. Chun & Jiang (1998) report that participants demonstrated a significant 5% accuracy increase for repeating contexts (78.5%) when compared to unique contexts (73.5%).

Jiang and Wagner (2004) tested whether participants were cued by the complete visuospatial context or with individual locations of items within the context. Participants were trained on a set of 36 repeating contexts and 18 target locations. Thus, two repeating contexts had the same target location. After a training period where participants searched through repeating and unique contexts, participants completed a transfer session. During the transfer session, participants were tested on all of the repeating contexts from the training period, a set of unique contexts, and a set of hybrid contexts. Because there was a single target location shared between two repeating contexts, half of the items that composed one repeating context were combined with half of the items that composed the second repeating context that shared the same target location. Thus, if contextual cueing is the result of learning the entire context, then the response times for the original repeating contexts should be faster than the hybrid contexts. However, if contextual cueing is the result of learning only parts of repeating contexts, the response times for the hybrid contexts should be approximately equal to the original repeating contexts. The results indicate that only a subset of the spatial configuration of repeating contexts were used to obtain a cueing effect.

Indeed, Jiang and Wagner were surprised that contextual cueing occurred in the hybrid contexts. The authors questioned if the entire visuospatial pattern of displayed repeating contexts is *ever* learned (Jiang & Wagner, 2004). Participants were initially trained on a set of repeating contexts to the point that a robust cueing effect was established. After training, participants were tested on the same repeating contexts; however, they were now displaced or rescaled. Scaling and displacing a repeating context changes the exact item locations (i.e. Euclidean coordinate) while maintaining the relative visuospatial relationship of the repeating context. It is unclear why this was tested, as Chun and Jiang (1998) demonstrated that random distractor jitter did not reduce cueing effects. Not surprisingly, Jiang and Wagner found that cueing was maintained for the rescaled and displaced repeating contexts. The authors conclude that two types of context learning occur: (1) the "pattern" of associations between items composing a repeating context is learned and paired with the target location and (2) the association between each item composing a repeating context and the target location is learned.

Song & Jiang (2005) conducted three experiments to determine the minimum number of unchanging item locations necessary to elicit cueing effects. In the first two experiments, participants were trained on a set of repeating contexts interleaved with unique contexts, each containing 12 items (11 distractors and 1 target). After establishing a reliable cueing effect, participants were tested in a transfer phase that included new *semi-repeating contexts* that matched the repeating contexts from training across a range of item locations. The new semi-repeating contexts contained either 1 identical item location (target location only), 2 identical item locations (target location + 1 distractor location), 3 identical item locations (target location + 2 distractor locations), 4 identical item locations (target location + 3 distractor locations), or all 12 identical items locations (i.e., repeating context). The results indicate that at least 3 item locations from a previously viewed repeating context are necessary to evoke a reliable contextual cueing effect that is just as robust as the one established during training.

In their third experiment, Song & Jiang (2005) tested if contextual cueing effects could be acquired during training with only 3 unchanging item locations (target location + 2 distractor locations) and 9 varying distractor locations in repeating contexts. The results indicate that varying 9 item locations in repeating contexts during training does not produce a contextual cueing effect. The authors conclude that a strong "matching signal" (Song & Jiang, 2005, p. 329) constructed during the learning phase is necessary to build up a stable memory representation that reliably cues the target's location. The authors hypothesize that a "similarity index" is calculated to determine the match between a currently viewed context and one stored in memory, and the similarity calculation can be based on the entire context or a subset thereof (Song & Jiang, 2005). These processes must occur within 600-800 ms as demonstrated in experiment 5 by Chun and Jiang (1998, p. 54, Table 5)

Peterson and Kramer (2001) conducted experiments to examine the extent to which the capture of attention by abrupt onset distractors would disrupt the acquisition and use of memory-based attention guidance, as in contextual cueing. In the first experiment, abrupt onset distractors were introduced at the beginning of practice on the search task. Response time results indicated that onset distractors and repeating contexts had independent and opposing influences on the efficiency of search. In the third experiment, abrupt onset distractors were introduced after repeating contexts effectively cued target location. In this case contextual cueing partially suppressed the detrimental influence of the abrupt onset distractors on search performance within repeating contexts. Peterson and Kramer (2001) provide evidence that contextual cueing effects suppress, or override, exogenous influences such as attentional capture.

In summary, contextual cueing is an example of the cognitive system capitalizing on environmental regularities, such as when item locations composing a context repeat across trials. Cueing continues to occur after training when only a subset of items repeat (at least 3), when item features at item locations within contexts are changed (e.g., from "B "to "3"), and when item locations are rescaled or randomly jittered. Contextual cueing does not occur when a small subset of items (3) repeat across views of repeating contexts during training or when abrupt onsets occur during training. Finally, eye movements have been deemed unnecessary to obtain benefits from contextual cueing after contextual cueing is established.

1.3.3 FAST and Contextual Cueing

The current section highlights synergies between FAST and contextual cueing research. First, the contextual cueing paradigm is adequate for testing FAST. To test FAST, a paradigm that satisfies 3 criteria must be adopted: (1) the paradigm must contain multiple repeating stimuli across several trials; (2) each repeating stimulus must be independent and associated with a specific goal (e.g., visual search); (3) the paradigm must use adequate controls with which to compare visual scans from repeating stimuli, such as multiple unique stimuli. The contextual cueing paradigm satisfies all three criteria.

Second, the contextual cueing phenomena can be simply explained as a by-product of behavioral mechanisms hypothesized in FAST, providing an alternative account of the cueing process to that hypothesized by Chun and colleagues. FAST maintains that visual scans are functional and can be adapted through a behavior-refinement process. To claim evidence for FAST, three criteria must be met: (1) scan patterns must repeat and become increasingly similar across repeated searches through the same stimulus independent of the number of saccades comprising scans, (2) the number of saccades comprising scans must be reduced to complete a goal with increased experience, and (3) scan patterns from repeating contexts must become more similar at a faster rate than scan patterns from unique contexts.

First, the generally accepted theory of the contextual cueing phenomenon is covered. Next, an alternative theory is provided with FAST. The section closes with specific scanning hypotheses derived from FAST within the contextual cueing paradigm.

1.3.3.1 Previously Proposed Theory of Contextual Cueing

Generally, contextual cueing is hypothesized to require a "… powerful and sophisticated memory … to encode and maintain distinctive representations of such rather homogeneous displays." (Chun & Jiang, 1998, p. 33), and to rely "… on a highly discriminative instance-based memory for spatial configurations." (Chun & Jiang, 1998, p. 38). Furthermore, Chun and Jiang postulate, "… that contextual cueing is driven by a beneficial interaction between an instance-based visual memory and spatial attention rather than the facilitation of perceptual and attentional processing per se." (1998, p. 39). Chun and Jiang invoke "context maps" as a new type of instance-based memory store for visual memory traces of context (1998, p. 39). This hypothesis follows from the passive approach flavor to studying the visual system – once the eyes absorb a stimulus, it is transmitted to the cognitive system, where "instance-based visual memory" and "spatial attention" "interact" and result in "context maps," which are then stored for later use. If this were the case, why would eyes ever need to move? The current theory does not contain adequate accounts of instance-based visual memory and context maps. Moreover, instance-based visual memory and context maps could be red herrings with regard to the underlying processes of contextual cueing.

Jiang and Wagner (2004) continue to postulate the mechanisms behind contextual cueing, and seem to be moving toward an active vision account. The authors suggest that associations, "… between the target and each individual distractor may be acquired because of the serial manner of conjunction search…The distractors visited prior to finding the target become potentially predictive of where the target is." (2004, p. 457). This hypothesis suggests that the relative spatial arrangement of items is necessary, and that over "… repeated navigation within the same environment, the subjects may gradually integrate discrete, isolated locations into one spatial schema. They might then rely more on the relative distractor locations than on isolated distractor–target associations to locate the target." (Jiang & Wagner, 2004; pp. 462).

Finally, Song & Jiang (2005, p. 329) ask "What is the mechanism that allows the visual system to determine the match between an incoming display and a previous memory?" and answer:

> "…we believe that a similarity index is calculated: A new display is compared with previous memory instance [sic]. The more similar the two displays are, the more likely the visual system will rely on the retrieved memory to find the target. The calculation of similarity can be based on the entire configuration (how similar the whole display is to a previous memory configuration), or on a subset of the configuration, or even individual locations (Jiang & Wagner, 2004). Whether similarity is calculated on the basis of global display characteristics or on local features remains to be tested. Nonetheless, the degree of match needs to be higher during the initial learning phase before a strong memory trace is established."

Clearly, this response is framed in the passive vision approach. A stimulus is absorbed through the eyes and transmitted through the cognitive system as a context map. The new context map is somehow compared to many (millions, billions, trillions) previously computed context maps, each containing some number of common item locations. The comparisons are intended to determine the similarity between the current and stored context maps. Arguably, this hypothesis suggests that if the maps are *similar*, the response location is retrieved; however, there is neither a proposed mechanism for determining similarity, nor speculation of *how similar* context maps must be before cueing occurs. Yet another question arises: does the comparison occur *during* or *after* terminating search? Moreover, how long do these processes take to execute? Finally, do the eyes move during these processes or are they merely *laying in wait*? And, if they do move, what effect does this have on the developing context map, the similarity computation between the developing context map and stored maps, and resultant context map retrieval?

Never is a concrete contextual cueing mechanism proposed or tested; rather, more and more studies are suggested to narrow down the underlying mechanisms – it seems like the leading proponents of contextual cueing are playing 20 questions with nature, and losing (Newell, 1973).

1.3.3.2 A FAST Account of Contextual Cueing

The phenomenon of contextual cueing has been studied and explained through the passive vision approach. The following passage can be used to elucidate the limits to understanding visual phenomena using only the passive approach to vision research:

> "Behavior is guided and constrained by the stimulus environment but, at any given moment, there are an overwhelming number of objects and events competing for visual awareness and control of action. This is the well-known problem of information overload…If bottom-up visual cues are not always useful, then what cues exist to guide visual selection? One strong candidate is visual context, a factor that is present in almost all acts of everyday perception" (Chun, 2000, p. 170).

Chun (2000) seems to miss the point that goals can, and do, drive visual behavior. Furthermore, this passive approach to contextual cueing seems to have failed at discriminating the underlying cueing mechanisms.

The mechanisms leading to cueing may be revealed through an active vision approach, such as FAST. For instance, it is possible that the similarity comparisons that Song and Jiang (2005) allude to are actually shifts of attention that result in repeating scan patterns across a stimulus. As visual attention shifts from location to location, the eyes move across a stimulus acquiring information at each location (Godijn & Pratt, 2002). Memory retrievals could occur to retrieve a target location that was previously found using the same shifts of attention/scanning pattern. This notion is similar to recalling information about an imagined stimulus via saccades across the imagined stimulus (Laeng & Teodorescu, 2002). Without an active vision approach to contextual cueing, this hypothesis would never be considered or tested.

FAST will also help to identify underlying processes influencing contextual cueing. As discussed earlier there are three influences affecting saccades–exogenous, endogenous, and statistical. Such influences are statistical in nature, where endogenous and exogenous are opposing extremes of the statistical influence spectrum (see Figure 1). The influences vicariously affect scanning patterns through individual saccades.

Behavior from purely endogenous influences would not be refined, even though alternative endogenous strategies could, and probably would, exist. Endogenous influences would either occur after learning had ceased (i.e., such as a settled on and deliberate strategy), or repeatedly using the same scan pattern on the same stimulus after the initial view of the stimulus, as predicted by scanpath theory. Behavior from purely exogenous influences would not be refined, because they are, by definition, void of learning. The same stimulus would always influence scan patterns in the same manner, leading to repeating scan patterns.

Although it would be difficult to differentiate between endogenous and exogenous influences, it is possible to detect differences between statistical and endogenous influences, and statistical and exogenous influences. Indeed, as experience with a task environment and a paired goal increase, repeating scan patterns may shift from what appears to be more exogenous to what appears to be more endogenous, though the pattern(s) may never become explicit or consciously executed. Interestingly, Chun and Jiang (1998) have convincingly demonstrated that contextual cueing is an implicit process.

Given the connection between FAST and the contextual cueing paradigm and phenomenon clear predictions about visual scan patterns in the contextual cueing paradigm are now possible. The predictions can be divided into predictions about visual scans across repeating and unique contexts. Unique contexts have repeating target locations, so there is a small degree of environmental stability that the cognitive system can use to its advantage. Repeating contexts have a very high degree of environmental stability. Although unique contexts are not truly unique, they still provide a good control group of contexts to compare against changes in scan patterns from repeating contexts. Predictions derived from FAST are: (1) the number of saccades to find the target will be reduced across repeating and unique contexts, (2) visual scan patterns will increase in similarity across repeated searches through repeating and unique contexts, independent of the number of saccades comprising scans, and (3) scan patterns from repeating contexts will increase in similarity at a greater rate than scan patterns from unique contexts because more information repeats in repeating contexts than in unique contexts.

1.4 Summary of Introduction & Historical Review

Cognitive functions are influenced through mechanisms that are sensitive to statistical properties of the functional task environment (Anderson & Schooler, 1991; Gray, Neth, & Schoelles, in press). Endogenous and exogenous influences represent extreme degrees of statistical influences from the environment. Statistical influences are mediated through a strict cognitive cost-benefit accounting of behavior in terms of time (Gray & Fu, 2004; Gray, Sims, Fu, & Schoelles, 2006), and have been shown to influence visual attention (Reder, Weber, Shang, & Vanyukov, 2003) and saccades (Myers & Gray, submitted).

Influences affecting single saccades can be scaled up to understand how sequences of saccades, or visual scans, are affected by deliberate strategies, statistical properties of the functional task environment, and stimulus features comprising the task environment. Indeed, scan patterns can repeat across the same stimulus (Josephson & Holmes, 2002; Pieters, Rosbergen, & Wedel, 1999). Scanpath theory postulates that repeating scan patterns result only from stored information (i.e., purely endogenously influenced, Noton & Stark, 1971a, 1971b). Finally, repeating scan patterns are functional to recalling information stored in memory about a previously viewed scene (Brandt, Stark, Hacisalihzade, Allen, & Tharp, 1989; Laeng & Teodorescu, 2002).

Functionally adaptive scanning was introduced as a theory of when and how repeated scan patterns change. FAST assumes that visual scan patterns repeat across multiple searches through the same stimulus. Furthermore, FAST assumes that visual scans play a functional role during tasks, as in providing cues for recalling the location of task relevant information. Unlike scanpath theory, FAST predicts that repeating scan patterns will be refined across repeated uses to reduce the amount of time to complete the goal (i.e., find a target) while maintaining accuracy.

Contextual cueing research reported by Chun (2000) and neurocognitive scanpath research reported by Grosbras et al. (2001) hail known neural correlates of memory (i.e., the hippocampal and parahippocampal areas) as integral to repeating scan patterns and contextual cueing. Although this does not provide evidence of causation, it also does not rule out the possibility of the same neural mechanism being involved in both phenomena.

The contextual cueing paradigm is well suited for testing FAST. Moreover, FAST provides an alternative theory to the contextual cueing phenomenon. FAST predictions of visual scanning in the contextual cueing paradigm are: (1) visual scan patterns will increase in similarity across repeated searches through repeating and unique contexts, independent of the number of saccades comprising scans, (2) the number of saccades to find the target will be reduced across repeating and unique contexts, and (3) scan patterns from repeating contexts will increase in similarity at a greater rate than scan patterns from unique contexts.

2. Empirical Investigations

Three experiments were conducted to test FAST using the contextual cueing paradigm. All experiments were designed to determine if scan patterns repeat and are refined across multiple searches through repeating contexts. The first experiment was also conducted to counter Chun & Jiang's conclusion that "contextual cueing can be obtained without eye movements" (1998, p. 56). There are problems with Chun & Jiang's eye movement controls, and experiment 1 improves on them. Experiment 1 results should be similar to Chun & Jiang's experiment 5 (1998) if eye movements are unnecessary to elicit contextual cueing effects. The second experiment tested subtle paradigm differences between experiment 1 and Chun & Jiang's experiment 5 to determine if the differences contributed to experiment 1 results. Experiment 3 tested effects of cognitive load within the contextual cuing task to examine influences on scanning patterns.

2.1 Experiment 1

There were two goals of experiment 1. The first goal was to determine if repeating scan patterns are refined across multiple searches through repeating contexts. The second goal was to demonstrate that eye movements are necessary to elicit contextual cueing. Chun and Jiang (1998) present evidence that eye movements are unnecessary to elicit contextual cueing after cueing has been established; however, Chun and Jiang did not adequately control for eye movements. The following section reprises Chun and Jiang's (1998) method for determining if eye movements are unnecessary for contextual cueing. Next, experiment 1 method is contrasted to Chun and Jiang's method, followed by the results and conclusions of the experiment.

2.1.1 Experiment 1 Methods

Chun & Jiang (1998, experiment 5) attempted to rule out the proceduralization of repeating scan patterns as the contextual cueing mechanism. Participants were instructed to find a target among distractors and respond to the target's orientation. Participants performed three phases of trials: training, testing-practice, and testing. Participants exhibited a contextual cueing effect by the end of the training phase.

Trials in the testing phases (testing-practice and testing) were different from those in the training phase. In the training phase, participants could exhaustively search the stimulus for the target and then respond. In the testing phases, the stimulus was flashed to participants, remaining visible for only 200 ms. The brief stimulus presentation was believed to be an adequate eye movement control. Once the stimulus disappeared, the display remained blank until participants responded with the target's direction. After responding, a new trial began. In the testing-practice phase, participants completed only unique context trials. In the testing phase, participants completed trials of repeating and unique contexts.

The key comparison to show that eye movements are unnecessary to benefit from established contextual cueing was the accuracy levels between repeating and unique contexts from the testing phase. Chun & Jiang report that participants achieved a significant 5% increase in accuracy for repeating contexts (78.5%) when compared to unique contexts (73.5%). Indeed, Chun & Jiang (1998) found a marked decline in accuracy – from a mean of 99% correct in the training phase to a mean of 74% correct in the testing phase. Finally, it is clear that participants' response times lasted well beyond the offset of the stimulus (≈ 600 ms, Chun & Jiang, 1998, p. 54, Table 5). Chun and Jiang conclude that the proceduralization of repeating scan patterns could not contribute to the cueing effect.

The 200 ms stimulus presentation was presumed to control for eye movements. Rather, it controls for the duration the stimulus is presented and participants are free to move their eyes. Indeed, participants took ≈ 810 ms to respond to the stimulus. If the average dwell time is taken to be ≈ 200 ms and the average saccade time to be ≈ 25 ms, then ≈ 3.5 saccade-dwell pairs can be completed before a response is made. The method for the current experiment uses a slightly modified version of Chun and Jiang's (1998) method (*minimum-control*) and adds a second between-participants condition (*maximum-control*) that improves eye movement controls throughout a trial and presents visual masks during feedback.

2.1.1.1 Experiment 1 Task Overview

As in Chun and Jiang's experiment 5 (1998), participants were to locate a target (T) among distractors (L) and respond as quickly and accurately as possible to the target's orientation. First, participants fixated crosshairs on a dwell control display for 600 ms. The crosshairs were gaze-contingent–changing from green to red when the participant was not staring at them, and changed back to green when the participant returned gaze to the crosshairs. Gaze contingency was introduced to provide real-time feedback that participants needed to fixate the crosshairs when their gaze shifted away from the crosshairs. After 600 ms, a stimulus with 11 distractors and 1 target was presented and participants were to find the target as quickly and accurately as possible. After responding to the target's orientation, accuracy feedback was provided to the participant (see Figure 4).

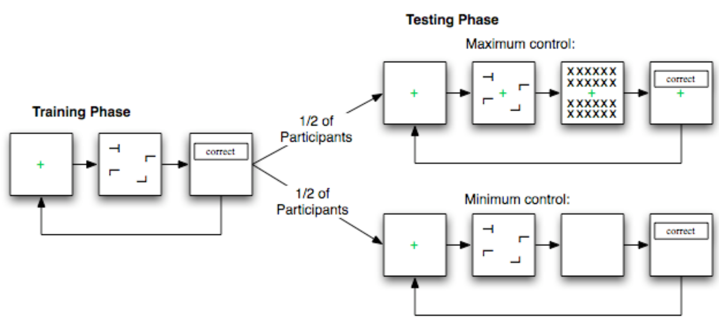

Figure 4. Experiment 1 flow. Participants began the experiment in the training phase and were transferred to the testing phase after completing 20 blocks of trials. Participants were randomly assigned to either the minimum- or maximum-control groups.

Participants completed 3 phases: training, testing-practice and testing. Participants performed 20 blocks (1 block = 24 trials) in the training phase, 2 blocks in the testing-practice phase, and 10 blocks in the testing phase. Each block contained 12 repeating and 12 unique contexts, presented in random order (excluding the 2 blocks of the testing-practice phase which only used unique contexts). After completing the 20th block of training, all participants were transferred to the testing-practice phase, and then to the testing phase.

2.1.1.1.1 Experiment 1 Design

Experiment 1 used a 2(dwell-control) x [2(phase) x 2(context-type)] mixed experimental design. There were two between-participant dwell control groups (maximum-control, minimum-control) that each started with the training phase and moved to a testing phase, and searched through repeating and unique contexts (see Figure 4).

The minimum-control group's testing phase was a slightly modified version of Chun & Jiang's method. In experiment 1, the minimum-control group was allowed to move their eyes about a stimulus during its 200 ms presentation. After the stimulus disappeared, a blank display was presented to participants until a response was given. After the participant issued a response, accuracy feedback was presented visually (e.g., "correct" or "incorrect") for 1 second followed by the initial fixation display constituting the beginning of a new trial. The only difference between the minimum-control group testing-phase and Chun and Jiang's (1998, experiment 5) testing-phase were gaze-contingent crosshairs instead of a non-gaze-contingent black dot.

The maximum-control group's testing-phase differed considerably from Chun & Jiang's testing phase in two important ways. First, gaze-contingent crosshairs were present on *all displays* in the maximum-control testing phase condition, and helped to ensure eye movements did not occur at anytime throughout a trial. Second, a visual mask was presented after stimulus presentation. After the 200 ms stimulus presentation, a mask appeared in the form of a 30 x 30 grid of 'X's along with the gaze-contingent crosshairs. Participants were instructed to continue looking at the crosshairs and respond as accurately as possible to the orientation of the target. Indeed, accuracy was stressed. Once a participant responded, accuracy feedback was provided and lasted for 1 second (see Figure 4).

The minimum-control group's testing phase was very similar to Chun and Jiang's (1998), while the maximum-control group had more eye movement controls. If the proceduralization of eye movements is not the mechanism behind contextual cueing, then both the minimum- and maximum-control conditions should duplicate Chun and Jiang's experiment 5 results (1998). One could argue that introducing gaze-contingent crosshairs when a context is flashed for 200 ms alters the context enough that benefits from contextual cueing would not occur; however, contextual cueing remains robust after training when context rescaling occurs (Jiang & Wagner, 2004), changes occur in distractor locations (Song & Jiang, 2005), contexts are hybridized (Jiang & Wagner, 2004), and salient abrupt-onset distractors are presented (Peterson & Kramer, 2001).

2.1.1.2 Apparatus

2.1.1.2.1 Task Environment

The task environment was built in-house using ANSI common Lisp in the LispWorks development environment. The task environment ran on Apple Macintosh OS 10.4.4.

Each stimulus configuration contained 12 items, eleven "L" and one "T". Items were oriented in either the 90° or 270° position. Participants responded to the direction of the "T" using a Cedrus® response pad by pressing *right* if the T's top was on the right, and *left* if the top was on the left (see Figure 5). Stimuli were presented on a 17" flat-panel display at a resolution of 1280 x 1024. Each item subtended ≈ 2° of visual angle. The center of all items was separated by a minimum of ≈ 3° of visual angle at a viewing distance of ≈ 22 inches. Consequently, the minimum distance between items was ≈ 1° of visual angle.

A single trial consisted of three displays. First, a participant fixated crosshairs (+) on the dwell control display to ensure that all participants began searching from the center of the display. After 600 milliseconds, the stimulus display appeared whether or not participants' gaze was on the crosshairs. The participant completed the trial by finding and responding to the target's (T) direction (right or left). Responses were captured using a Cedrus© response box (see Figure 5). After participants' response, accuracy feedback was provided and lasted for 1 second (see Figure 4).

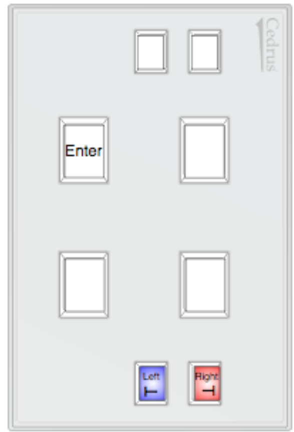

Figure 5. Cedrus response pad configuration. Participants responded to a target's (T) orientation by pressing the blue, left button if the T's top was facing leftward, otherwise they responded by pressing the red, right button.

2.1.1.2.2 Eye Tracker

A binocular Eyegaze Analysis System©, manufactured by LC Technologies, Inc., was used to track participants' point-of-gaze. The system has a 120 Hz sampling rate and is accurate to 0.45° of visual angle (0.15 inch) at a distance of ≈ 22 inches. The system runs on Microsoft Windows XP and communicates with the task environment over a TCP/IP connection.

2.1.1.3 Participants

A total of 42 students from Rensselaer Polytechnic Institute consented to participate in the experiment. Appropriate experiment credit was provided to each participant.

2.1.1.4 Procedure

After signing an informed consent form, each participant was randomly assigned to a testing-phase group. Next, each participant was given the appropriate task instructions. Following instructions, each participant was calibrated to the eye tracker. Next, participants completed the 20 blocks (480 trials) of the training phase. Participants took a mandatory 10-second break after each block of 24 trials, as in Chun and Jiang (experiment 5, , 1998). After completing the training phase, each participant was presented with the appropriate testing phase instructions and completed 2 blocks (48 trials) of the testing-practice phase, composed solely of unique contexts. After the testing-practice phase trials, each participant completed the testing phase (10 blocks; 240 trials).

2.1.2 Experiment 1 Results

First, results will be presented on gaze position control during the dwell control display. Second, accuracy and response times are reported for the training phase, followed by accuracy and response time analyses for the testing phase. Finally, scan pattern analyses are presented. The 48 speeded-response practice trials were excluded from all analyses.

2.1.2.1 Experiment 1 Training Phase

Gaze control, accuracy, and response time analyses are reported in the following sections. Outliers were determined for each analysis using 2 standard deviations from the mean as a criterion for removal.

2.1.2.1.1 Experiment 1 Training Phase: Gaze Control

A 2(task-type) x [2(context-type) x 20(block)] mixed analysis of variance (ANOVA) was conducted to determine if there were systematic differences in the ability to fixate crosshairs on the dwell control display (gaze control) during the training phase that are attributable to the independent variables used in experiment 1. The dependent variable was the mean proportion of trials that resulted in the crosshairs being dwelled at the time of stimulus presentation within a block. All participants were included as there were no outliers. Block, and the context-type x block interaction, violated sphericity, thus the Greenhouse-Geisser correction was used (see Table A1).

There was not a main effect of context-type [$F(1,34) = 0.14$; $p = 0.72$, *NS*)] indicating no difference in gaze control between repeating and unique contexts. There was a significant main effect of block [$F(4.68,159.21) = 2.75$, $p = 0.023$] where the mean proportion of trials beginning with dwelled crosshairs on the dwell control display across blocks decreased from a mean of 0.974 in block 1 to a mean of 0.927 in block 20. There was also a significant main effect of task-type (minimum-control, maximum-control) [$F(1,34) = 12.913$; $p = 0.001$)], where the maximum-control group had a greater proportion of trials that began with participants staring at the crosshairs ($M = 0.986$) than the minimum-control group ($M = 0.921$).

2.1.2.1.2 Experiment 1 Training Phase: Trial Accuracy

A 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was conducted to determine if there were systematic differences in response accuracy that are attributable to the independent variables. Two participants were removed from the maximum-control group as they exceeded 2 standard deviations below the mean level of response accuracy, leaving 19 participants in the maximum-control group and 21 participants in the minimum-control group. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used (see Table A2).

There were no significant effects associated with any of the independent variables, and the mean proportion of correct trials remained high across all twenty blocks of the training phase ($M = 0.982$). The main effect of context-type was not significant [$F(1,38) = 0.39$; $p = 0.53$, *NS*), nor was block [$F(9.591,364.44) = 1.11$; $p = 0.36$, *NS*), nor was the main effect of task-type [$F(1,38) = 2.11$; $p = 0.16$, *NS*). The context-type X block interaction was not significant [$F(11.7,444.46) = 0.67$; $p = 0.78$, *NS*).

2.1.2.1.3 Experiment 1 Training Phase: Response Time

A 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on response times from correct trials. Two participants were removed, one from each task group, as they exceeded 2 standard deviations from the mean response time on correct trials, leaving 20 participants in the minimum-control group and 20 participants in the maximum-control group. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geiser correction was used (see Table A3).

There was a significant main-effect of block [$F(4.51,166.95) = 25.92$; $p < 0.001$), where response times were gradually reduced from a mean of 1525.92 ms in block 1 to a mean of 1115.9 ms in block 20. There was not a main effect of context-type [$F(1,37) = 0.78$; $p = 0.38$, *NS*)] or of task-type [$F(1,37) = 1.76$; $p = 0.19$, *NS*)]. The context-type x block interaction was not significant [$F(8.55,316.3) = 1.54$; $p = 0.19$, *NS*)].

The non-significant context-type x block interaction shows that contextual cueing was not present given the above set of analyses; however, Chun and Jiang (1998) analyzed their data differently. Instead of analyzing response times as a function of block, they averaged response times from 5 blocks into an *epoch*. Consequently, there were 4 epochs in their training phase. Chun and Jiang then performed the analysis on the response times from only epochs 1 and 4. Chun and Jiang report "a trend toward significance" for the context-type x epoch interaction (1998).

Following from Chun and Jiang's (1998) analyses, a 2(task-type) x [2(context-type) x 2(epoch)] mixed ANOVA was performed on response times from correct trials. The same two participants removed from the analyses above were removed from the current analysis, leaving 20 participants in the minimum-control group and 20 participants in the maximum-control group. There was a significant context-type x epoch interaction on response times, with repeating context response times decreasing at a faster rate than unique contexts from epoch 1 ($M_{Repeating}$ = 1317.9; M_{Unique} = 1281.3) to epoch 4 ($M_{Repeating}$ = 1122; M_{Unique} = 1142), indicating the presence of contextual cueing [$F(1, 38) = 4.6$, $p = 0.038$] (see Table A4).

2.1.2.2 Experiment 1 Training Phase Results Summary

First, participants had a high proportion of trials that began with staring at the crosshairs, as instructed. Although participants' ability to fixate the crosshairs decreased across epochs, participants maintained a high level of dwell control throughout the experiment– 95% of trials began with the appropriate gaze location. Second, participants were regularly accurate with their responses, never dropping below 97% accuracy. Finally, and most importantly, repeating contexts were responded to at an increasingly faster rate than unique contexts from epoch 1 to epoch 4 as evidenced by the significant epoch (1, 4) x context-type (repeating, unique) interaction. The interaction reproduces the key results from Chun and Jiang's experiment 5 training phase (1998). If eye movements *do not* contribute to contextual cueing, then both the maximum-control and minimum-control conditions should reproduce Chun and Jiang's experiment 5 testing phase accuracy results (1998). However, if eye movements facilitate contextual cueing, then there will not be a significant main effect of context-type on accuracy in the maximum-control condition, but will be significant in the minimum-control condition.

2.1.2.3 Experiment 1 Testing Phase

There were only two epochs in the testing phase so the gaze control, response times, and accuracy analyses used a 2(task-type) x [2(context-type) x 10(block)] mixed ANOVA.

2.1.2.3.1 Experiment 1 Testing Phase: Gaze Control

A 2(task-type) x [2(configuration-type) x 10(block)] mixed ANOVA was conducted to determine if there were systematic differences in the ability to fixate the crosshairs on the dwell control display during the testing phase. Five participants were removed, 1 from the minimum-control group and 4 from the maximum-control group, as they exceeded 2 standard deviations from the mean proportion of trials beginning with gaze centered on the crosshairs. This left 20 participants in the minimum-control group and 17 participants in the maximum-control group. Block, and the context-type x block interaction, violated sphericity, thus the Greenhouse-Geisser correction was used (see Table A5).

There was not a main effect of context-type [$F(1, 35) = 0.0834$, $p > 0.77$, *NS*] or of block [$F(2.82, 100.89) = 0.231$, $p > 0.86$, *NS*]. However, there was a main effect of task-type [$F(1, 35) = 7.85$, $p = 0.008$], where the minimum-control group ($M_{Min} = 0.85$) had a smaller proportion of testing phase trials beginning with gaze centered on the dwell control display crosshairs than the maximum-control group ($M_{Max} = 0.98$). This result shows that the added eye movement controls in the maximum-control group (gaze contingent crosshairs throughout a trial) helped to ensure that participants maintained their gaze where they were instructed when a stimulus appeared. No other effects were significant

2.1.2.3.2 Experiment 1 Testing Phase: Response Times

Although participants in the minimum-control group did not always maintain gaze on the crosshairs when the stimulus was presented, Chun and Jiang did not test for gaze control and included all correct trials into analyses of response time and accuracy regardless of gaze position at stimulus onset. Consequently, all correct trials from both conditions were included in analyses. There were three outliers removed from analyses, all from the maximum-control group, leaving 18 participants in maximum-control and 21 participants in minimum-control. Block, and the context-type x block interaction, violated sphericity, thus the Greenhouse-Geisser correction was used.

A 2(task-type) x [2(context-type) x 10(block)] mixed ANOVA was conducted to determine if there were systematic differences in response times during the testing phase (see Table A6). There was not a main effect of context-type [$F(1, 37) = 1.41$, $p > 0.24$, *NS*] nor was there a main effect of task-type [$F(1, 37) = 1.41$, $p > 0.29$, *NS*]. There was a main effect of block [$F(4.32, 159.69) = 2.56$, $p = 0.037$] where the first block of testing after testing-practice was significantly slower in the mean response time ($M = 871$ ms) when compared to the last block ($M = 791.9$ ms). The mean response times for the testing phase ($M = 819$ ms) is only 11-12 ms higher than those reported by Chun and Jiang (1998, experiment 5): epoch 5 = 806.5 ms and epoch 6 = 807.5 ms. There was not a significant context-type x block interaction [$F(4.89, 181.89) = 0.93$, $p > 0.6$, *NS*]

2.1.2.3.3 Experiment 1 Testing Phase: Trial Accuracy

Chun and Jiang report an accuracy benefit in repeating contexts during their testing phase and conclude that the increased accuracy is due to contextual cueing established during the training phase. The dependent variable of interest is the proportion of correct responses; consequently, correct and incorrect trials were included. Again, following Chun and Jiang's lead, all trials from the minimum-control group were included in analyses even though this group was significantly worse at controlling their gaze position at stimulus onset than the maximum-control group. There were three outliers removed from analyses, all from the maximum-control group, leaving 19 participants in maximum-control and 20 participants in minimum-control.

A 2(task-type) x [2(context-type) x 10(block)] mixed ANOVA was performed on the proportion of correct trials (see Table A7). There was not a main effect of context-type [$F(1, 37) = 0.001$, $p > 0.97$, *NS*], nor was there an main effect of block [$F(9,333) = 0.75$, $p > 0.66$, *NS*], nor was there a main effect of task-type [$F(1, 37) = 2.13$, $p > 0.15$, *NS*]. There was not a significant context-type x block interaction [$F(9, 333) = 0.71$, $p > 0.69$, *NS*].

2.1.2.4 Experiment 1 Testing Phase Results Summary

There are two important results from experiment 1. First, when analyzing as a function of block, contextual cueing was absent. However, when aggregating blocks of trials into epochs of trials (as in Chun & Jiang, 1998), the effect was present.

Second, participants' responses were not more accurate to repeating contexts than to unique contexts from the testing phase. Moreover, there were no accuracy differences between the minimum- and maximum-control groups. Furthermore, task-type did not interact with context-type (repeating and unique) suggesting that improved eye movement controls (maximum-control) did not affect responses within repeating and unique contexts any differently than the minimum-control condition. Finally, the results did not duplicate Chun and Jiang's experiment 5 results (1998) – there was no advantage in response accuracy for repeating contexts in the testing phase.

2.1.2.5 Experiment 1 Scan Pattern Analyses

A contextual cueing effect was found in the training phase of experiment 1. This result was present when aggregating blocks of trials into epochs of trials, but was not present when leaving trials aggregated at the block level. Indeed, Chun and Jiang's (1998) response time analyses did not reveal a cueing effect. Although it would be ignorant to conclude that contextual cueing is an effect that comes and goes with the tides based on experiment 1 and Chun and Jiang (1998), it is possible that response time is not sensitive enough to always detect cueing. An alternative measure to response times is the similarity and refinement of scan patterns.

According to FAST, there are 3 criteria of visual scan refinement that lead to 3 specific predictions within the contextual cueing paradigm: (1) the number of dwells to find the target will be reduced across repeating and unique contexts, (2) scan patterns will repeat on repeating contexts, and will increase in similarity across repeated searches through repeating and unique contexts, independent of the number of saccades/dwells comprising scans, and (3) scan patterns from repeating contexts will increase in similarity at a greater rate than scan patterns from unique contexts.

The current section presents visual scan analyses to test for scanning refinement during the training phase of experiment 1. The following section presents the method for computing visual scan similarities. Next, the results from the scan pattern analyses are presented. Finally, scan pattern conclusions are drawn from the results.

2.1.2.5.1 Method for Comparing Visual Scan Patterns

ProtoMatch software (Myers & Schoelles, 2005) was used to delineate dwells into visual scans from the point a stimulus was displayed until a response was provided. ProtoMatch is a data analysis software tool that reads in a file of all relevant experiment information regarding (e.g., display items and point of gaze) collected during the experiment. ProtoMatch calculates dwells using a sample-based fixation algorithm (see Myers & Schoelles, 2005, for a full description of the algorithm). Once a dwell is calculated the closest display item within 2° of visual angle is assigned to the dwell. If there is not a display item within 2° of visual angle, "no display item" is assigned to the dwell. After computing all dwells, dwell sequences were divided into trials producing a visual scan for each trial.

To determine the degree of similarity between two visual scans, the sequence alignment module within ProtoMatch was used for determining minimum-edit distances between two strings. The core of this module is the Levenshtein distance algorithm (Levenshtein, 1966) that takes a visual scan (S_1) and determines the minimum number of insertions, deletions and replacements (edits) necessary to change it into another scan (S_2). For example, to change "FIREMAN" (S_1) into "POLICEMAN" (S_2) the algorithm's solution would 1) insert a "P" to the left of the "F"; 2) insert "O" to the left of the "F"; 3) replace "F" with "L", and 4) replace "R" with "C". Therefore, the minimum-edit distance for changing "FIREMAN" into "POLICEMAN" is 4.

Replacing the letters in the FIREMAN-POLICEMAN example with the order of items viewed (i.e., "F" = [first dwelled object] "I" = [second dwelled object] "R" = [third dwelled object], etc.) from a visual scan provides an example of how scans are compared using the Levenshtein algorithm. The alignment algorithm is similar to the minimum-edit algorithms used by Salvucci & Anderson (2001) and Fu (2001), discussed in Card et al. (1983), and is a simplified version of algorithms used in bioinformatics (Thompson, Higgins, & Gibson, 1994) and other scanning research (Josephson & Holmes, 2002).

Once the minimum-edit distance between two scans is returned from the Levenshtein algorithm, it is normalized to control for differences in lengths of compared visual scans (Josephson & Holmes, 2002), providing a normalized dissimilarity index (NDI):

$$NDI = \frac{MED}{S_{longest}} \tag{1}$$

where *MED* is equal to the raw minimum-edit distance from the two compared scans divided by the number of dwells from the longest of the two scans ($S_{longest}$). The NDI represents the maximum dissimilarity between two visual scans.

It is important to use the NDI rather than the raw MEDs because a raw MED of 6 from two sequences may actually signify greater similarity than a raw MED of 6 from two different sequences. For example, suppose sequence *A* is 10 items long and sequence *B* is 4 items long and their minimum edit distance is 6. Now suppose that sequence *C* is 20 items long and sequence *D* is 14 items long and their minimum edit distance is 6. Going by the raw MED scores one would conclude they were equally similar. However, after dividing by the longest sequence the *CD* NDI is 0.30 while the *AB* NDI is 0.60. Here, one would conclude that sequences *A* and *B* are more dissimilar to each other than sequences *C* and *D*. Simply, a greater NDI refers to greater dissimilarity between compared sequences. Subtracting 1 from the NDI can be done to obtain the normalized degree of similarity, or NSI.

$$NSI = 1 - NDI \tag{2}$$

The following analyses use the NSI metric to compute scan pattern similarity differences between repeating and unique contexts across and within participants.

The experiment design provides guidance on how to aggregate and compare scan patterns. Because repeating contexts were searched through once per block, visual scans were aggregated into epochs of blocks (1 epoch = 5 blocks). For each participant, repeating contexts within each epoch (5 views of the same repeating context) were compared against each other producing 10 NSIs that were then averaged to obtain the mean epoch NSI for each of the 12 repeating contexts. Next, the mean NSI for each epoch was averaged across repeating contexts to acquire the mean repeating context NSI for each epoch. The same process was applied to unique contexts, but because their targets repeated, unique contexts were only compared with other unique contexts that had the same target location. This effectively mimicked the process for computing the repeating context NSIs (see Figure 6).

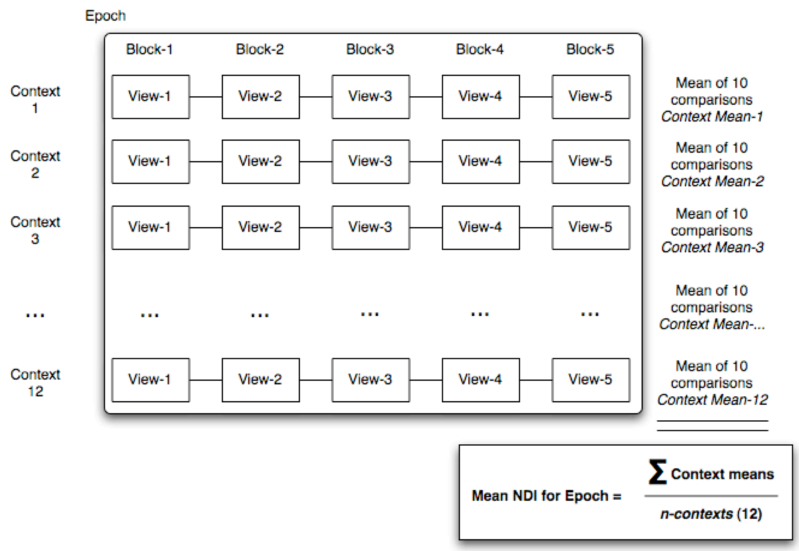

Figure 6. Computing mean NSIs for each epoch of trials.

2.1.2.5.2 Scanning Analyses for Experiment 1

To determine if visual scans were refined across repeated searches through repeating contexts, NSIs were computed for each type of context for each participant. There were 20 analyzable blocks of 24 trials (4 epochs) in the training phase of experiment 1, and the analyses are directed toward determining if all FAST criteria are present in the experiment 1 training phase.

2.1.2.5.2.1 Criterion 1: Dwell Reduction across Repeated Search

ProtoMatch software was used to calculate dwells, determine the items associated with each dwell, and calculate dependent measures associated with dwells and associated objects, such as dwell durations. Simply, a dwell is steady gaze positioning within 2° of visual angle for at least 100 ms (see Myers & Schoelles, 2005, for a full description of the algorithm). After removing outliers, there were 18 maximum-control participants and 17 minimum-control participants for each of the following analyses.

If the number of dwells to find a target is reduced across blocks of trials, then there is support for FAST's second criterion. A 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on the mean number of dwells to find the target per block. Block, and the context-type x block interaction, violated sphericity, thus the Greenhouse-Geisser correction was used (see Table A8).

The main effect of context-type was not significant [$F(1, 33) = 3.18$, $p = 0.083$, *NS*]. There was a main effect of block [$F(8.29, 294.67) = 24.03$, $p < 0.001$], where the mean number of dwells to find the target was reduced across blocks ($M_{Block\text{-}1} = 3.97$; $M_{Block\text{-}20} = 2.77$) but there was not a main effect of task-type [$F(1, 33) = 1.392$, $p > 0.24$, *NS*]. There was not a significant context-type x task-type interaction [$F(1, 33) = 0.24$, $p > 0.62$, *NS*], nor was there a significant block x task-type interaction [$F(8.29, 294.67) = 0.82$, $p > 0.59$, *NS*], nor was there a significant context-type x block interaction [$F(10.79, 355.99) = 1.35$, $p = 0.20$, *NS*. The main effect of block supports FAST's first criterion of visual scan refinement: dwell reduction across blocks of trials.

More support for the first criterion comes from *re-dwells,* re-encoding previously encoded information within the same visual scan. If visual scans are being refined, re-dwells should be reduced across blocks. A 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on the proportion of stimulus items (distractors or targets) assigned to more than one dwell, per trial (see Table A9). Only dwells assigned to display items were used. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used.

There was not a main effect of context-type [$F(1,33) = 0.33$, $p > 0.56$, *NS*], nor was there a main effect of task-type [$F(1,33) = 1.39$, $p > 0.24$, *NS*]. Importantly, there was a main effect of block [$F(7.48, 246.66) = 2.18$, $p = 0.033$], where re-dwells were significantly reduced across blocks ($M_{Block\text{-}1} = 0.08$; $M_{Block\text{-}20} = 0.03$). There was not a significant context-type x block interaction [$F(10.79, 355.99) = 1.05$, $p > 0.39$, *NS*]. The main effect of block on re-dwells provides further support for FAST's first criterion of visual scan refinement.

2.1.2.5.2.2 Criteria 2 & 3: Scan Pattern Similarity Increases Independent of Dwell Reduction & Patterns from Repeating Contexts Increase at a Faster Rate than Patterns from Unique Contexts

Scan pattern analyses were conducted to determine if FAST criteria 2 and 3 were present in experiment 1. According to FAST, scan patterns will repeat on repeating contexts, and will increase in similarity across repeated searches through repeating and unique contexts independent of the number of saccades/dwells comprising scans (Criterion-2), and scan patterns from repeating contexts will increase in similarity at a greater rate than scan patterns from unique contexts (Criterion-3). The NSI metric, described above, was used for computing similarity. If the second criterion is present, then there should be a significant main effect of epoch on NSIs. If the third criterion is present, then there should be a significant context-type x epoch interaction where repeating contexts increase in similarity at a faster rate across epochs than unique contexts.

To determine if there were differences in NSIs between repeating and unique contexts across epochs, a 2(task-type) x [2(context-type) x 4(epoch)] mixed ANOVA was performed on all mean NSIs (see Table A10). After removing outliers, there were 18 fixed-view participants and 17 free-view participants. Only dwells that were assigned a display item were used in the NSI calculation. Epoch violated the sphericity assumption, and any results reported that are associated with epoch use the Greenhouse-Geisser correction.

There was a main effect of context-type [$F(1, 33) = 111.73$; $p < 0.001$] where repeating contexts ($M_{Repeating} = 0.66$) were significantly more similar than unique contexts ($M_{Unique} = 0.59$). There was a main effect of epoch [$F(2.08, 68.75) = 54.75$; $p < 0.001$] demonstrating an increase of similarity across epochs. There was not a significant context-type x epoch interaction [$F(3, 99) = 1.89$; $p = 0.137$, *NS*] (see Figure 7).

The above analyses did not reveal evidence supporting FAST's 3rd criteria: scan patterns from repeating contexts did not increase at a faster rate than patterns from unique contexts. Indeed, post-hoc analyses using the Bonferonni correction revealed that there were significant differences in NSIs between repeating and unique contexts in the first epoch ($p < 0.001$). Perhaps a very fast increase in similarity occurred in the first epoch. A new analysis was performed to determine if aggregating data into epochs washed out the interaction. The new analysis is a *step-wise* similarity comparison between subsequent views of contexts. For example, the first scan pattern (S1) from a repeating context was compared to the second scan pattern (S2) from the same repeating context (S1vS2). Then, S2 was compared to the third scan pattern (S3) from the same repeating context. The first six views were compared for all repeating contexts. The same was done for unique contexts with the same target location. In total, there were 5 step-wise comparisons for both types of contexts (i.e., S1vS2, S2vS3, S3vS4, S4vS5, S5vS6). After computing step-wise NSIs, they were averaged across each context for repeating contexts and repeating target locations for unique contexts, providing average step-wise comparison NSIs for each comparison (e.g., S1vS2) for both context-types (i.e., repeating and unique).

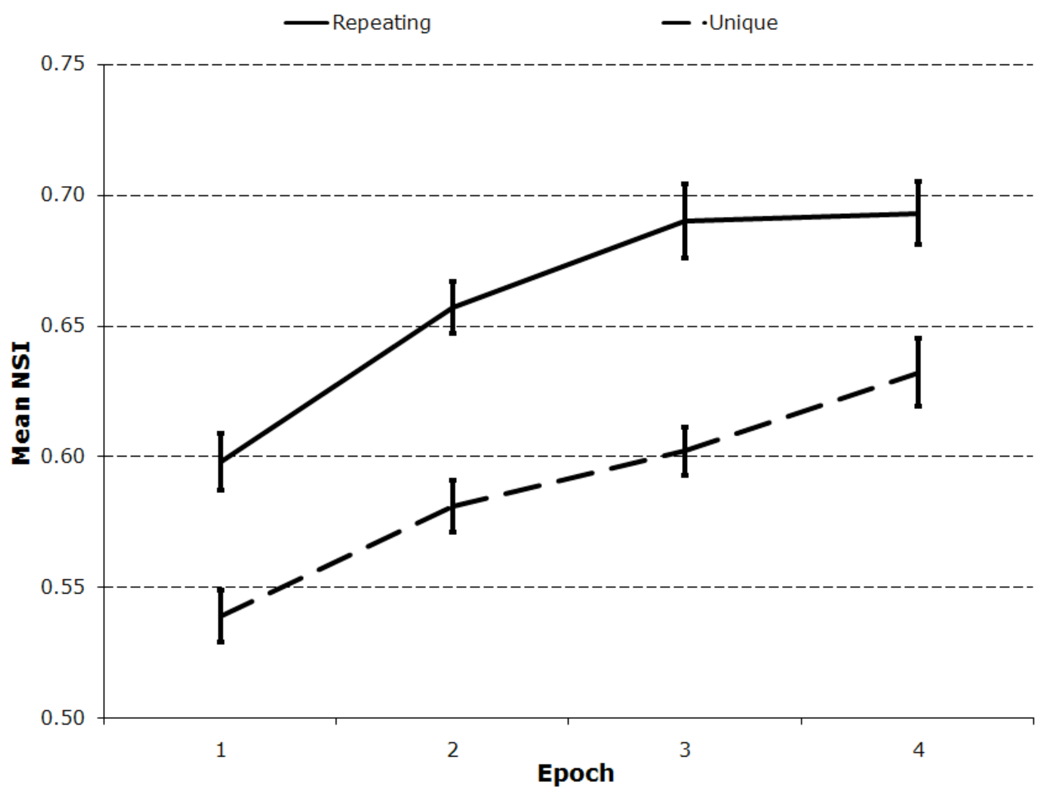

Figure 7. Experiment 1 scan pattern similarity results. Mean NSI as a function of epoch and context-type (repeating, unique). Error bars represent 95% confidence intervals.

To determine if there were differences in NSIs between repeating and unique contexts across step-wise comparisons, a 2(task-type) x [2(context-type) x 5(comparison)] mixed ANOVA was performed on all mean step-wise NSIs (see Table A11). There was a significant main effect of context-type [$F(1, 34) = 5.27$; $p = 0.028$]. There was not a main effect of comparison [$F(4, 34) = 0.17$; $p > 0.95$], nor was there a main effect of task-type [$F(1, 34) = 0.5245$; $p > 0.47$, *NS*]. There was not a context-type x comparison interaction [$F(4, 136) = 0.41$; $p > 0.79$, *NS*]. The results of the step-wise analysis did not reveal an interaction between context-types and step-wise comparisons.

2.1.2.6 Dwell Duration Analyses

Although FAST makes no claims about dwell durations, they were analyzed for completeness. To determine if dwell durations changed as a function of context-type, task-type, or block, a 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on all dwells (both assigned to display items, and those unassigned to display items were included) (see Table A12). Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geiser correction was used. There was not a significant main effect of context-type [$F(1,33) = 1.85$, $p > 0.18$, *NS*]. There was not a main effect of task-type [$F(1,33) = 0.001$, $p > 0.975$, *NS*]. There was a significant main effect of block [$F(6.94, 228.9) = 4.89$, $p < 0.001$], where dwell durations decreased from block 1 (238.32 ms) to block 20 (198.9 ms). There was not a significant context-type x block interaction [$F(10.77, 355.48) = 1.02$, $p > 0.42$, *NS*].

2.1.3 Experiment 1 Conclusions

With some statistical "effort," a contextual cueing effect was found in the training phase of experiment 1. Although the effect was not present when aggregating trials into blocks, the effect was present when aggregating blocks of trials into epochs of trials, and only analyzing the first and last epoch of trials from the training phase, just as Chun and Jiang did in their experiment 5 (1998).

Chun and Jiang (experiment 5, , 1998) presented evidence that eye movements were unnecessary for eliciting benefits after establishing a contextual cueing effect in the training phase–responses to repeating contexts were more accurate than responses to unique contexts during the testing phase (see Table 1). The current experiment was designed to duplicate these results in the minimum-control group, even though there were subtle differences between the methods used in the minimum-control group and those used by Chun and Jiang. Experiment 1 also increased eye movement controls in the maximum-control condition. One hypothesis from experiment 1 was that participants' testing phase response accuracy for repeating contexts would be higher than unique contexts in the minimum-control condition, but would not differ in the maximum-control condition. There were no differences in accuracy between repeating and unique contexts in either the minimum- or maximum-control conditions or between the two conditions (see Table 1). The results from the minimum-control group, where eye movements were more likely to occur, did not duplicate the results from Chung and Jiang (1998). This result does not support their claim that eye movements are unnecessary to benefit from an established cueing effect.

Table 1. Accuracy results from Chun & Jiang (1998) and Experiment 1 testing phases.

Experiment	Context-type		Mean
	Repeating	Unique	
Chun & Jiang (1998)	0.785	0.735	0.760
Experiment 1			
Maximum-control	0.712	0.725	0.719
Minimum-control	0.755	0.741	0.748

The results from the scan pattern analyses mostly support FAST. The first criterion of FAST, a reduction in the number of dwells to find the target across repeated searches, was supported in experiment 1. The second criterion of FAST, an increase in scan pattern similarity independent of the number of dwells to find the target across repeated searches, was also supported by experiment 1 results. The third hallmark of FAST, scan patterns from repeating contexts increase in similarity at a faster rate when compared to scan patterns from unique contexts, was not supported by experiment 1 results. Furthermore, the step-wise scan pattern comparison analyses show that scan patterns from repeating contexts are more similar than scan patterns from unique contexts after the first two views, as predicted by scanpath theory.

One possible limitation of experiment 1 was the presentation of a visual mask after the stimulus presentation in the maximum-control condition. The mask was presented to help reduce movements of visual attention across a retinal afterimage. Laeng and Teodorescu (2002) demonstrated that scan patterns across an imagined stimulus aid in recalling information about the imagined stimulus, and the mask was used to impede this process in the testing phase of experiment 1. Chun and Jiang did not include masks because performance was “already quite low without further disruption of the presentations, suggesting that internal representations of the displays had rapidly faded.” (1998, p. 54).

Indeed, it is unclear what role, if any, the mask played in hindering contextual cueing benefits in testing phase of the maximum-control group. Interestingly, accuracy levels from the minimum-control condition were not significantly different from levels from the maximum-control condition, and both were similar to the accuracy of responses to unique contexts from Chun and Jiang (1998). This similarity in response accuracy between the unique contexts in the minimum-control condition (where a mask was not used) and Chun and Jiang's unique contexts suggest that differences between the two did not create large differences in response accuracy (see Table 1).

Surprisingly, Chun and Jiang's results were not duplicated in the minimum-control condition–there was not a repeating-context accuracy benefit even though neither of the two gaze controls from the maximum-control condition were used (i.e., dwell control crosshairs on all trial displays and the mask). This is inconsistent Chun and Jiang's experiment 5 results used as evidence that eye movements are unnecessary for contextual cueing.

To summarize, 2 out of 3 FAST criteria were supported in experiment 1. Although the 3rd criterion was not present in the results, experiment 1 provides initial evidence for FAST. A contextual cueing effect was found after some statistical "effort;" however, there were no differences between repeating or unique contexts during the testing phase. Contrary to Chun and Jiang's (1998) results, results from experiment 1 do not support the hypothesis that eye movements are not needed for contextual cueing to occur. One possibility leading to no differences between repeating and unique contexts in the minimum-control condition is that the gaze-contingent dwell control crosshairs on the dwell control display acted as a subtle, yet reliable, dwell control beyond that used by Chun and Jiang (i.e., a solid black circle). Experiment 2 tests this hypothesis.

2.2 Experiment 2

In experiment 1, a contextual cueing effect was established during the training phase. During the experiment 1 testing phase, the proportion of correct trials did not differ between repeating and unique contexts in either the minimum- or maximum-control conditions.

Unfortunately, Chun and Jiang's results were not duplicated in the experiment 1 condition most similar to their experiment 5 methods, minimum-control. Gaze-contingent dwell-control crosshairs may have acted as a subtle eye movement control beyond that used by Chun and Jiang (a static black circle). Experiment 2 manipulates crosshair gaze-contingency between groups of participants to determine if gaze-contingent crosshairs on the dwell control display, only, provide enough eye movement control during stimulus presentation to eliminate testing-phase response accuracy benefits of repeating contexts reported by Chun and Jiang (1998). Experiment 2 provides further opportunity to test each of FAST's criteria.

2.2.1 Experiment 2 Methods

2.2.1.1 Experiment 2 Task Overview

The task was similar to experiment 1: participants were to locate a target (T) among distractors (L) and respond as quickly and accurately as possible. Participants performed 768 trials, broken into 32 blocks, where each block was a set of 24 trials. As in experiment 1, each block contained 12 repeating and unique contexts. After completing the 20^{th} block, all participants were transferred to a testing phase.

2.2.1.1.1 Experiment 2 Design

The design of experiment 2 more closely replicated Chun and Jiang's (1998) experiment 5 than did experiment 1, where Chun and Jiang attempted to rule out the contribution of eye movements to contextual cueing. Experiment 2 used a 2(gaze-contingency) x [2(context-type) x 32(block)] mixed design, with 2 between participant dwell control crosshairs conditions (gaze-contingent and static), 2 within-participant configuration-types (repeating and unique) and 32 blocks.

Participants were randomly assigned to either gaze-contingent crosshairs (GC) or static crosshairs (STC). All participants' completed 20 blocks of 480 trials in the training phase (20 blocks of 24 trials – 12 repeating and 12 unique contexts per block). The training phase was the same as the training phase from experiment 1. First, a participant initially fixated crosshairs (+) on the dwell control display to ensure that all participants started search from the display center on all trials. The crosshair's color were gaze-contingent in the GC group, but were constantly green in the STC group. After 600 milliseconds, the stimulus display appeared (regardless if participants' gaze was on the crosshairs) and the participant completed the trial by finding and responding to the target's (T) orientation (right or left). Responses were captured using a Cedrus© response box (see Figure 5). After participants' response, accuracy feedback was provided and lasted for 1 second. Participants took a 10 second break after each block of 24 trials. After the training phase, participants' completed the testing phase.

During the testing phase, all participants were instructed to dwell on '+' at the center of the dwell control display. In the STC group, the crosshairs were always green. However, in the GC group, if participants' gaze deviated from the crosshairs, they changed from green to red. Once gaze returned to the crosshairs, they changed back to green. Gaze contingency was used to provide real-time feedback that participants needed to fixate the crosshairs when their gaze moved from the crosshairs. The gaze-contingent crosshairs were only present on the dwell-control display. After the 200 ms stimulus presentation, a blank display appeared. Participants were instructed to respond to the direction the target was facing as accurately as possible. Indeed, accuracy was stressed. Once a participant responded, accuracy feedback was provided and lasted for 1 second.

The only difference between the GC and STC groups was that the STC groups' crosshairs on the dwell control display remained green whether participants' gaze was on the crosshairs or away from them. The STC group is closest to the method used in Chun and Jiang's (1998) experiment 5, where the STC group has static green crosshairs and Chun and Jiang used a static black dot.

2.2.1.2 Experiment 2 Apparatus

2.2.1.2.1 Task Environment

The task environment was identical to experiment 1, with the changes presented above.

2.2.1.2.2 Eye Tracker

The same eye tracker used in experiment 1 was used in experiment 2.

2.2.1.3 Experiment 2 Participants

A total of 40 students from Rensselaer Polytechnic Institute participated in the experiment. A total of 1 hour of experiment credit was provided as compensation to all who completed the task.

2.2.1.4 Experiment 2 Procedure

After signing an informed consent form, each participant was randomly assigned to a gaze-contingency group. Next, each participant was given the appropriate task instructions. Following instructions, each participant was calibrated to the eye tracker. Next, participants completed 20 blocks (480 trials) of the training phase. Participants took a mandatory 10-second break after each block of 24 trials, as in Chun and Jiang (1998) experiment 5. After completing the training phase, each participant was presented with testing phase instructions and completed 2 blocks (48 trials) of unique contexts for the testing-practice phase. After the testing-practice phase, each participant began the final 10 blocks (240 trials) of the experiment in the testing phase.

2.2.2 Experiment 2 Results

First, results will be presented on gaze position control at the onset of the stimulus (i.e., context). Second, accuracy and response times are reported for the training phase, followed by gaze position control, response time, and accuracy analyses for the testing phase. Finally, scan pattern analyses are presented. The 48 speeded-response practice trials were excluded from all analyses.

2.2.2.1 Experiment 2 Training Phase

Gaze control, accuracy and response time analyses from the training phase are reported in the following sections.

2.2.2.1.1 Experiment 2 Training Phase: Gaze Control

A 2(gaze-contingency) x [2(context-type) x 20(block)] mixed ANOVA was conducted to determine if there were systematic differences in the ability to fixate crosshairs on the dwell control display (gaze control) during the training phase that are attributable to the independent variables used in experiment 2. The dependent variable was the mean proportion of trials that resulted in the crosshairs being dwelled at the time of stimulus presentation, per block. After removing outliers, there were 19 participants in the STC group and 18 participants in the GC group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used.

There was not a main effect of context-type [$F(1,35) = 0.32$; $p > 0.57$, *NS*)] indicating no difference in gaze control between repeating and unique contexts. There was not a significant main effect of block [$F(5.25,183.86) = 0.99$, $p > 0.42$, *NS*], nor was there a main effect of task-type (GC, STC) [$F(1,35) = 0.041$; $p = 0.84$, *NS*]. Context-type did not interact with block [$F(9.05, 316.58) = 0.99$, $p > 0.44$, *NS*]. (see Table B1). No effects were significant indicating that crosshair gaze contingency did not affect gaze control. The mean proportion of trials where participants were staring at the crosshairs when a stimulus appeared was high for both groups: $M_{STC} = M_{GC} = 0.95$.

2.2.2.1.2 Experiment 2 Training Phase: Trial Accuracy

A 2(gaze-contingency) x [2(context-type) x 20(block)] mixed ANOVA was conducted to determine if there were systematic differences in response accuracy during the training phase that are attributable to the independent variables used in experiment 2. The dependent variable was the proportion of correct trials, per block. After removing outliers, there were 19 participants in the STC group and 20 participants in the GC group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used.

There was not a significant main effect of context-type [$F(1,37) < 0.001$; $p > 0.99$, *NS*)] indicating no difference in response accuracy between repeating and unique contexts. There was not a significant main effect of block [$F(10.52,389.29) = 1.21$, $p > 0.28$, *NS*], nor was there a main effect of task-type (GC, STC) [$F(1,37) = 0.50$; $p > 0.48$, *NS*]. Task-type did not interact with block [$F(10.52,389.29) = 1.44$; $p > 0.15$, *NS*)] or context-type [$F(1,37) < 0.02$; $p > 0.89$, *NS*)]. Context-type did not interact with block [$F(10.9, 403.19) = 0.69$, $p > 0.73$, *NS*] (see Table B2). No effects were significant, indicating that, regardless of their gaze contingency, dwell control crosshairs did not affect response accuracy The mean proportion of correct responses was high for both groups: $M_{STC} = M_{GC} = 0.98$.

2.2.2.1.3 Experiment 2 Training Phase: Response Times

Experiment 1, and previous research (Chun & Jiang, 1998, experiment 5) has demonstrated that contextual cueing can occur within 480 trials. To determine if contextual cueing occurred within the training phase of experiment 2, a 2(gaze-contingency) x [2(context-type) x 20(block)] mixed ANOVA was conducted on response times. After removing outliers, there were 19 participants in the STC group and 18 participants in the GC group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used.

There was a significant main-effect of block [$F(7.31,255.7) = 25.92$; $p < 0.001$), where response times were gradually reduced from a mean of 1287.2 ms in block 1 to a mean of 943.6 ms in block 20. There was not a main effect of context-type [$F(1,35) = 0.12$; $p > 0.73$, *NS*)] or of task-type [$F(1,35) = 2.04$; $p > 0.16$, *NS*)]. The context-type x block interaction was not significant [$F(9.9,346.61) = 0.57$; $p > 0.83$, *NS*)] (see Table B3).

The contextual cueing effect did not occur in experiment 2. As in experiment 1, a 2(task-type) x [2(context-type) x 2(epoch)] mixed ANOVA was performed on response times from correct trials to determine if the effect was "hiding" as in experiment 1. The same participants removed from the response time analysis above were removed from the current analysis.

There was a significant main-effect of epoch [$F(1, 35) = 109.59$, $p < 0.001$] where response times in epoch 1 ($M = 1299.6$) were significantly slower than response times in epoch 4 ($M = 1132.4$). There was not a main effect of context-type [$F(1,35) < 0.01$; $p > 0.76$, *NS*)] or of task-type [$F(1,35) = 1.79$; $p > 0.18$, *NS*)]. There was not a context-type x epoch interaction [$F(1, 35) = 1.33$; $p > 0.26$, *NS*)]. These results show, without doubt, that contextual cueing did not occur during the training phase of experiment 3 (see Table B4).

2.2.2.2 Experiment 2 Training Phase Results Summary

Although contextual cueing occurred in experiment 1, experiment 2 participants failed to establish the effect during the training phase. It is unclear why contextual cueing did not occur; however, the absence of the effect provides an opportunity to test for differences in scan patterns between repeating and unique contexts when cueing does not occur. Before reporting results from scan pattern analyses, testing phase results will be reported. Because there was not a contextual cueing effect in the training phase, there should be no accuracy benefit for repeating contexts in the testing phase. Indeed, the accuracy results from both contexts in both groups should be equivalent to experiment 1 results and accuracy results from unique contexts in Chun and Jiang (1998, experiment 5).

2.2.2.3 Experiment 2 Testing Phase

Gaze control, response time, and accuracy analyses of testing phase data are reported in the following sections.

2.2.2.3.1 Experiment 2 Testing Phase: Gaze Control

A 2(gaze-contingency) x [2(context-type) x 10(block)] mixed ANOVA was conducted to determine if there were systematic differences in the ability to fixate crosshairs on the dwell control display (gaze control) during the testing phase that are attributable to the independent variables used in experiment 2. The dependent variable was the mean proportion of trials that resulted in the crosshairs being dwelled at the time of stimulus presentation, per block. After removing outliers, there were 18 participants in the STC group and 16 participants in the GC group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used.

There was not a main effect of context-type [$F(1,32) < 0.01$; $p > 0.95$, *NS*)] indicating no difference in gaze control between repeating and unique contexts. There was a significant main effect of block [$F(5.96,190.65) = 2.24$, $p = 0.041$], where gaze control fluctuated between blocks, and did not follow any particular trend or fall below 0.985 on any block (see Figure 8). There was not a main effect of task-type (GC, STC) [$F(1,32) < 0.01$; $p > 0.95$, $p = 0.84$, *NS*]. Context-type did not interact with block [$F(5.57, 178.26) = 0.72$, $p > 0.62$, *NS*] (see Table B5). The mean proportion of trials across blocks where participants dwelled the control crosshairs at the point a stimulus appeared was high for both groups: $M_{STC} = M_{GC} = 0.995$.

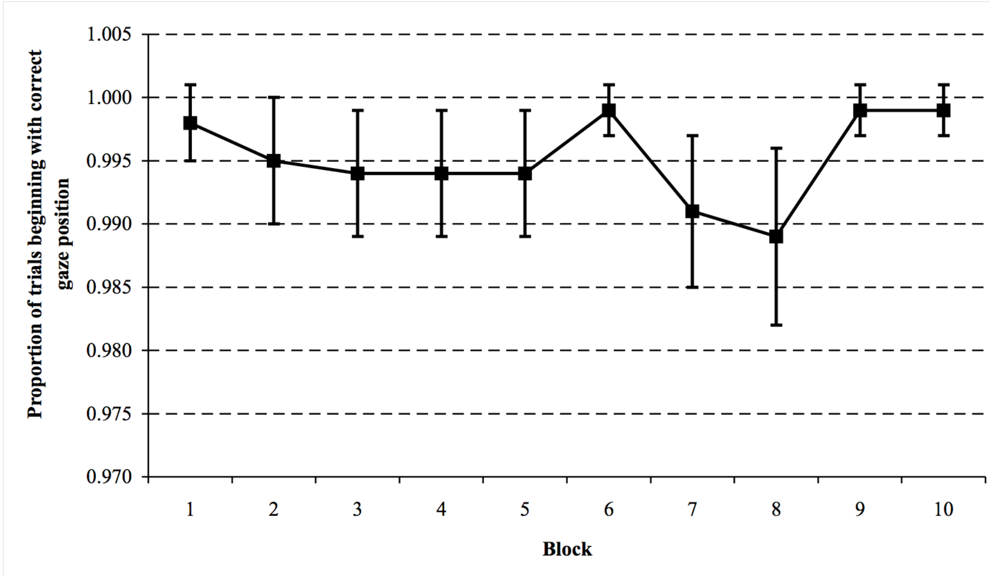

Figure 8. Experiment 2 testing-phase gaze-control as a function of block. Error bars are 95% confidence intervals.

2.2.2.3.2 Experiment 2 Testing Phase: Response Times

Because there was no difference between GC and STC groups on gaze controls when the stimulus was presented, all correct trials from the both conditions were included in the following analyses. After removing outliers, there were 18 participants in GC and 20 participants in STC. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geiser correction was used.

A 2(task-type) x [2(context-type) x 10(block)] mixed ANOVA was conducted to determine if there were systematic differences in response times during the testing phase (see Table B6). There was not a main effect of context-type [$F(1, 36) = 0.03$, $p > 0.85$, *NS*] nor was there a main effect of task-type [$F(1, 36) = 0.02$, $p > 0.88$, *NS*]. There was a main effect of block [$F(5.33, 191.8) = 5.87$, $p < 0.001$], where mean response times from the first block of testing was significantly slower ($M_{block\text{-}21}$ = 888 ms) when compared to the last block ($M_{block\text{-}30}$ = 777 ms). There was not a significant context-type x block interaction [$F(6.19, 222.66) = 1.32$, $p > 0.64$, *NS*].

2.2.2.3.3 Experiment 2 Testing Phase: Trial Accuracy

As in experiment 1, the dependent variable of interest is the proportion of correct responses; consequently, correct and incorrect trials were included. All trials from the minimum-control group were included in analyses. After removing outliers, there were 18 participants in GC and 20 participants in STC.

A 2(task-type) x [2(context-type) x 10(block)] mixed ANOVA was performed on the proportion of correct trials (see Table B7). There was not a main effect of context-type [$F(1, 36) = 0.065$, $p > 0.80$, *NS*]. There was a significant context-type x block interaction [$F(9, 324) = 2.26$, $p = 0.018$], where accuracy fluctuated across blocks, and did not follow an interpretable trend (see Figure 9).

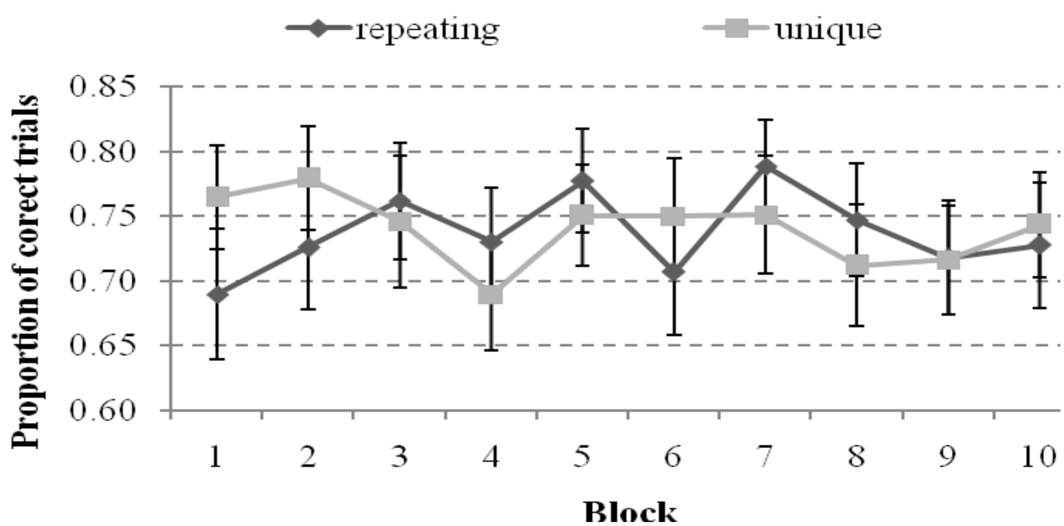

Figure 9. Response accuracy as a function of block in the experiment 2 testing phase. Error bars represent 95% confidence intervals.

2.2.2.4 Experiment 2 Testing Phase Results Summary

There are two key results from experiment 2. First, cueing was not established in the training phase as it was in experiment 1. Consequently, we did not duplicate Chun and Jiang's accuracy results in the testing phase of our NGC condition: repeating contexts were no more likely to result in a correct response than were unique contexts.

Table 2. Accuracy results from Chun & Jiang (1998) and experiment 1 and 2 testing phases.

Experiment	Context-type		Mean
	Repeating	Unique	
Chun & Jiang (1998)	0.785	0.735	0.760
Experiment 1			
Maximum-control	0.712	0.725	0.719
Minimum-control	0.755	0.741	0.748
Experiment 2			
Gaze contingent crosshairs	0.757	0.758	0.758
Static crosshairs	0.717	0.722	0.720

2.2.2.5 Experiment 2 Scan Pattern Analyses

To determine if visual scans were refined across repeated searches through repeating contexts, NSIs were computed for each type of context for each participant. There were 20 analyzable blocks of 24 trials (4 epochs) in the training phase of experiment 2, and the analyses are directed toward determining if all FAST criteria are supported in experiment 2.

The 3 criteria of FAST lead to 3 specific predictions within the contextual cueing paradigm: (1) scan patterns will repeat and increase in similarity across repeated searches through repeating and unique contexts independent of the number of saccades/dwells comprising scans, (2) the number of saccades to find the target will be reduced across repeating and unique contexts, and (3) scan patterns from repeating contexts will increase in similarity at a greater rate than scan patterns from unique contexts. The current section presents scan pattern analyses to test for scanning refinement during the training phase of experiment 2.

2.2.2.5.1 Criterion 1: Dwell Reduction across Repeated Search

As in experiment 1, ProtoMatch software was used to calculate dwells, assign stimulus items to dwells, and calculate dependent measures associated with dwells and associated objects. If FAST's second criterion of scan refinement occurred in experiment 1, the number of dwells to find a target should be reduced across blocks of trials in the training phase. A 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on all dwells (dwells paired and unpaired with display items were included). After removing outliers, there were 18 GC participants and 19 STC participants. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used (see Table B8).

There was not a main effect of context-type [$F(1, 35) = 0.485$, $p > 0.49$, *NS*]. There was not a main effect of transfer-task where GC and STC were equivalent ($M_{GC} = 2.89$; $M_{STC} = 2.83$) [$F(1, 35) = 0.14$, $p > 0.71$, *NS*]. Importantly, there was a main effect of block [$F(4.39,153.76) = 12.00$, $p < 0.001$] demonstrating that the number of dwells reduced across the 20 blocks of the training phase. There was not a significant context-type by block interaction [$F(9.67, 348.9) = 0.99$, $p > 0.45$, *NS*].

Further support for the second criterion can come from re-dwells. If visual scans are being refined, re-dwells should be reduced across blocks. A 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on the proportion of stimulus items (distractors or targets) assigned to more than one dwell, per trial, or re-dwells (see Table B9). Only dwells assigned to display items were used. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used.

There was not a significant main effect of context-type [$F(1,35) = 1.06$, $p > 0.31$, *NS*]. There was not a significant main effect of task-type [$F(1,35) = 0.27$, $p > 0.60$, *NS*]. There was a significant main effect of block [$F(6.93,242.38) = 4.52$, $p < 0.001$]. There was not a significant context-type x block interaction [$F(8.81,308.5) = 0.55$, $p > 0.83$, *NS*].

2.2.2.5.2 Criteria 2 & 3: Scan Pattern Similarity Increases Independent of Dwell Reduction & Patterns from Repeating Contexts Increase at a Faster Rate than Patterns from Unique Contexts

Visual scan analyses were conducted to determine if FAST criteria 2 and 3 were present in experiment 2. The NSI metric, used in experiment 1, was used for computing similarity. Support for the second criterion would come from a significant main effect of epoch on NSIs. Support for the third criterion would come from a significant context-type x epoch interaction where repeating contexts increase in similarity at a faster rate across epochs than unique contexts. Only dwells that were assigned a stimulus display item were used in the NSI calculation.

To determine if there were differences in NSIs between repeating and unique contexts across epochs, a 2(task-type) x [2(context-type) x 4(epoch)] mixed ANOVA was performed on all mean NSIs (see Table B10). After removing outliers, there were 18 GC participants and 19 STC participants. Epoch violated the sphericity assumption, and any results reported that are associated with epoch use the Greenhouse-Geisser correction.

There was a main effect of context-type [$F(1, 35) = 106.08$; $p < 0.001$] where repeating contexts ($M_{Repeating} = 0.67$) were significantly more similar than unique contexts ($M_{Unique} = 0.60$). There was a main effect of epoch [$F(2.18, 69.79) = 36.13$; $p < 0.001$] demonstrating an increase of similarity across epochs. There was not a significant main effect of task-type [$F(1, 33) = 1.16$; $p > 0.21$, *NS*]. There was not a significant context-type x epoch interaction [$F(3, 99) = 0.78$; $p > 0.49$, *NS*] (see Figure 10).

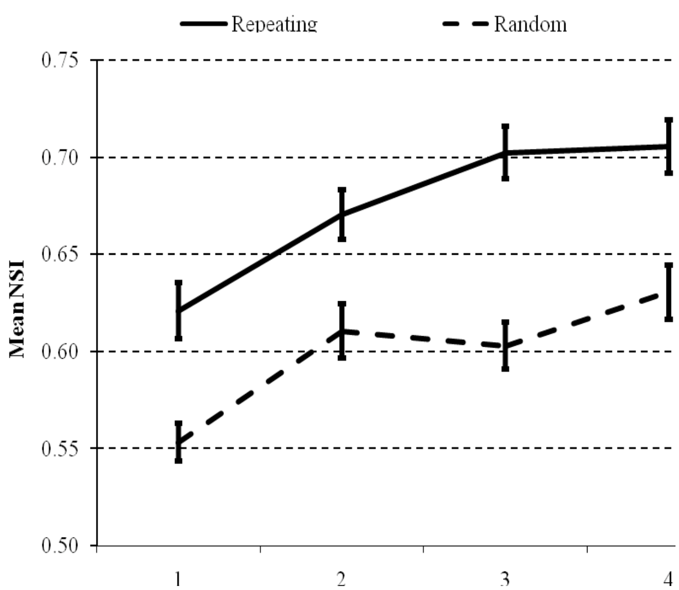

Figure 10. Experiment 2 scan pattern similarity results. Error bars represent 95% confidence intervals.

The above analyses did not reveal evidence supporting FAST's 3rd criteria: patterns from repeating contexts did not increase at a faster rate than scan patterns from unique contexts. Indeed, post-hoc analyses using the Bonferonni correction revealed that there were significant differences in NSIs in the first epoch from repeating and unique contexts ($p < 0.001$). Perhaps a rapid increase in similarity occurred in the first epoch. The same step-wise similarity analysis performed on experiment 1 data was performed on training phase eye data from experiment 2. As a reminder, the first scan pattern (S1) from a repeating context was compared to the second scan pattern (S2) from the same repeating context (S1vS2). Then, S2 was compared to the third scan pattern (S3) from the same repeating context. The first six views were compared for all repeating contexts. The same was done for unique contexts with the same target location. In total, there were 5 step-wise comparisons for both types of contexts (i.e., S1vS2, S2vS3, S3vS4, S4vS5, S5vS6). After computing step-wise NSIs, they were averaged across each context for repeating contexts and repeating target locations for unique contexts, providing average step-wise comparison NSIs for each comparison (e.g., S1vS2) for both context-types (i.e., repeating and unique).

To determine if there were differences in NSIs between repeating and unique contexts across step-wise comparisons, a 2(task-type) x [2(context-type) x 5(comparison)] mixed ANOVA was performed on all mean step-wise NSIs (see Table B11). There was a significant main effect of context-type [$F(1, 35) = 4.69$; $p = 0.037$]. There was not a main effect of comparison [$F(3, 105.14) = 0.22$; $p > 0.88$], nor was there a main effect of task-type [$F(1, 35) = 0.64$; $p > 0.43$, *NS*]. There was not a reliable context-type x comparison interaction [$F(4, 140) = 0.20$; $p > 0.93$, *NS*]. The results of the step-wise analysis did not reveal an interaction between context-types and number of times a context was viewed.

2.2.2.6 Dwell Duration Analyses

Although FAST does not make claims about dwell durations, they were analyzed for completeness. To determine if dwell durations changed as a function of context-type, task-type, or block, a 2(task-type) x [2(context-type) x 20(block)] mixed ANOVA was performed on all dwells (see Table B12). Block violated the sphericity assumption, thus the Greenhouse-Geisser correction was used. There was not a significant main effect of context-type [$F(1,35) = 0.14$, $p > 0.71$, *NS*]. There was not a main effect of task-type [$F(1,35) < 0.001$, $p > 0.98$, *NS*]. There was a significant main effect of block [$F(7.37, 257.95) = 3.06$, $p < 0.004$], where dwell durations decreased from block 1 (217.52 ms) to block 20 (190.9 ms). There was not a significant context-type x block interaction [$F(19, 665) = 0.63$, $p > 0.88$, *NS*].

2.2.3 Experiment 2 Conclusions

Repeating scan patterns are adopted in free-view paradigms. Experiment 1 showed that repeating scan patterns are also adopted during visual search, and experiment 2 duplicated the experiment 1 results. Contextual cueing is an example of adaptive behavior, where scene context is implicitly learned and used advantageously, resulting in faster response times in repeating contexts when compared to unique contexts. The discoverers and leading proponents of contextual cueing, M. Chun and Y. Jiang, assert that contextual cueing does not require eye movements. FAST maintains that scan patterns are repeated and refined, leading to improvements in tasks similar to the contextual cueing effect, and that eye movements are more than epiphenomenal. Experiments 1 & 2 were designed to challenge the assertion that contextual cueing does not require eye movements, and used an experiment method similar to the one used to demonstrate that eye movements are not linked to cueing effects (Chun & Jiang, 1998).

In experiment 1, participants exhibited contextual cueing by the end of the training phase; however, testing phase accuracy results did not duplicate the results reported by Chun and Jiang (1998). In experiment 2, participants did not exhibit contextual cueing effects by the end of the training phase. There was no difference between the task environments used for the gaze-contingent crosshairs condition (GC) of experiment 2 and the minimum-control condition from experiment 1. The only difference between the static crosshairs condition (STC) of experiment 2 and the minimum-control condition from experiment 1 was that the crosshairs were gaze contingent in minimum-control but not in STC. Consequently, it is unclear why contextual cueing would occur in experiment 1 and not occur in experiment 2. Nonetheless, the experiment 2 testing-phase was analyzed and the results duplicated the experiment 1 results. Interestingly and surprisingly, accuracy for repeating contexts never reached the level reported by Chun and Jiang (see Table 9). Furthermore, accuracy means from repeating and unique contexts in both conditions of experiment 2 were equivalent to the minimum-control condition from experiment 1 and greater than the results from the maximum-control condition. Based on the results from experiments 1 and 2, there is support that eye movements may be linked to contextual cueing.

Experiment 1 scan pattern analyses revealed that scan patterns from repeating contexts increase in similarity with experience, and that the number of dwells to find a target are reduced with experience, supporting FAST's first and second criteria, respectively. Scan patterns from experiment 2 qualitatively duplicated experiment 1 results. Unfortunately, the third hallmark of refinement, similarity of visual scans from repeating contexts increase at a greater rate with experience than scan patterns from unique contexts, was not present in either experiment, even after performing the step-wise scan pattern comparison analyses. However, the step-wise comparison analyses show that scan patterns are more similar from repeating contexts than scan patterns from unique contexts after the first two views, providing support for scanpath theory.

Although it would be ignorant to conclude that contextual cueing comes and goes with the tides based only on experiments 1 and 2, and Chun and Jiang (1998), it is possible that response time is not quite sensitive enough to reliably detect contextual cueing. An alternative dependent variable is the NSI metric used for determining scan pattern similarity. Indeed, experiment 2 provided an opportunity to determine if FAST's criteria were present when the contextual cueing effect was not captured using response times. The results from experiments 1 and 2 are interpreted as demonstrating the link between eye movements and contextual cueing. Moreover, the experiment results provide initial support for FAST. Although results from experiments 1 and 2 are mixed, 2 of FAST's 3 criteria were met in both experiments. It was unfortunate that contextual cueing was not established in experiment 2. To help ensure the occurrence of contextual cueing in experiment 3, the sizes of the stimulus items (targets and distractors) were reduced to limit the usefulness of peripheral vision during search. The logic here is that by limiting the ability to use peripheral vision, costs of search are increased due to the inability to encode information peripherally, creating the need to affix gaze on more display items to encode them and determine if they are the target. Not only might this help establish contextual cueing effects, it will also facilitate the visual scan analyses. Finally, experiment 3 contains a second task in the environment to determine the effect high load has on visual scans and contextual cueing, and is presented in the following section.

2.3 Experiment 3

Scan patterns repeat during free-view tasks. FAST maintains that scan patterns repeat and are refined in goal-oriented tasks. Experiments 1 and 2 demonstrate that scan patterns repeat, and are systematically refined with experience in goal-oriented tasks. Experiment 3 was conducted to further examine the role of repeating scan patterns in visual search using the contextual cueing paradigm. The experiment was also conducted to determine how increased cognitive load affects scanning and contextual cueing processes. Consequently, the method used in experiment 3 differed significantly from experiments 1 and 2.

2.3.1 Experiment 3 Methods

Experiment 3 differs from experiments 1 and 2 in four important ways. First, rather than having training and testing phases, experiment 3 does not have a testing phase. Contextual cueing was demonstrated in only one of the first two experiments, and that was with some 'statistical effort.' Experiment 3 extends the number of blocks from 20 to 30 (adding 240 trials) to help establish a contextual cueing effect, as measured by response time. The extra trials provided 10 more views of each repeating context compared experiments 1 and 2. If many views of repeating contexts are important for establishing contextual cueing, then experiment 3 provides more opportunity for contextual cueing to be established by the end of the experiment.

Second, the size of each stimulus item (distractors and targets) was made smaller than those used in experiments 1 and 2. The size reduction was to better test for the presence/absence of FAST's criteria. The size of stimulus items in experiments 1 and 2 were 2° of visual angle at a viewing distance of ≈ 22 in, and a minimum of 3° separated each item to ensure that all 12 items fit on the display and not overlap. Consequently, stimulus items in the first two experiments could be within 1° angle from each other. This small minimum distance enabled participants to encode multiple items without gazing at a single item. Reducing the stimulus item size in experiment 3 to 0.5° of visual angle makes it more difficult to encode multiple items with one dwell. Consequently, more stimulus items will be assigned to dwells in experiment 3 enabling better estimates of scan pattern similarities than those from experiments 1 and 2. If reducing the stimulus item size increases difficulty in encoding multiple items, then experiment 3 should have more dwells and more re-dwells to find the target than experiments 1 and 2.

Third, groups of participants searched through the same repeating contexts; whereas, in experiments 1 and 2, all repeating contexts were particular to individual participants. It is assumed in scanpath theory that repeating scan patterns are idiosyncratic between people, even when different people scan the same stimulus. Using the same repeating contexts across participants in experiment 3 helped to determine the similarity of scan patterns between participants on the same context. If different individuals' scan patterns from repeating contexts are truly idiosyncratic, then they should have NSIs approximately equal to scan patterns from unique contexts.

Fourth, cognitive load was manipulated between participants as a completely crossed cognitive load transfer task. Thus, there are 4 between participant groups that experience differences in cognitive load across 2 phases of the experiment. Participants will 1) start in a single-task phase and transfer to dual-task phase (SD), 2) start in a dual-task phase and transfer to single-task phase (DS), 3) start in a single-task phase and remain in single-task phase (SS), or 4) start in a dual-task phase and remain in the dual-task phase (DD). The SS and DD groups provide baselines of constant high and low load on contextual cueing and scan patterns.

Cognitive load was manipulated between groups to determine how periods of high cognitive load affect scan patterns and contextual cueing. If contextual cueing and repeating scan patterns are implicitly learned, then there should be little effect of cognitive load on trial response times or NSIs. Furthermore, effects of transferring from low-load to high-load on scan patterns and contextual cueing can be determined after repeating scan patterns have been adopted and while contextual cueing is becoming established. If contextual cueing and repeating scan patterns are implicitly executed, then there should be little effect of cognitive load on trial response times or NSIs when transferring from low to high cognitive load.

2.3.1.1 Experiment 3 Task Overview

Participants' were to locate a target (T) among distractors (L) and respond as quickly and accurately as possible. On each trial, there were 12 items on the screen, 11 distractors and 1 target. Participants performed 720 trials, broken into 30 blocks, where each block is a set of 24 trials. Each block contained 12 unique contexts and 12 repeating contexts presented in random order from block to block. After completing the 15th block, all participants took a mandatory 5-minute break. After the break, participants transferred into a single- or dual-task phase and completed the final 15 blocks.

2.3.1.1.1 Experiment 3 Design

Experiment 3 used a 4(load-transfer) x 3 (configuration-group) x [2(context-type) x 30(block)] mixed experimental design. There were four between-participant cognitive load transfer groups (SS, SD, DS, and DD) occurring across three configuration-groups that each searched through repeating and unique contexts across 30 blocks, where each block contained 24 trials (see Figure [E3-flow]).

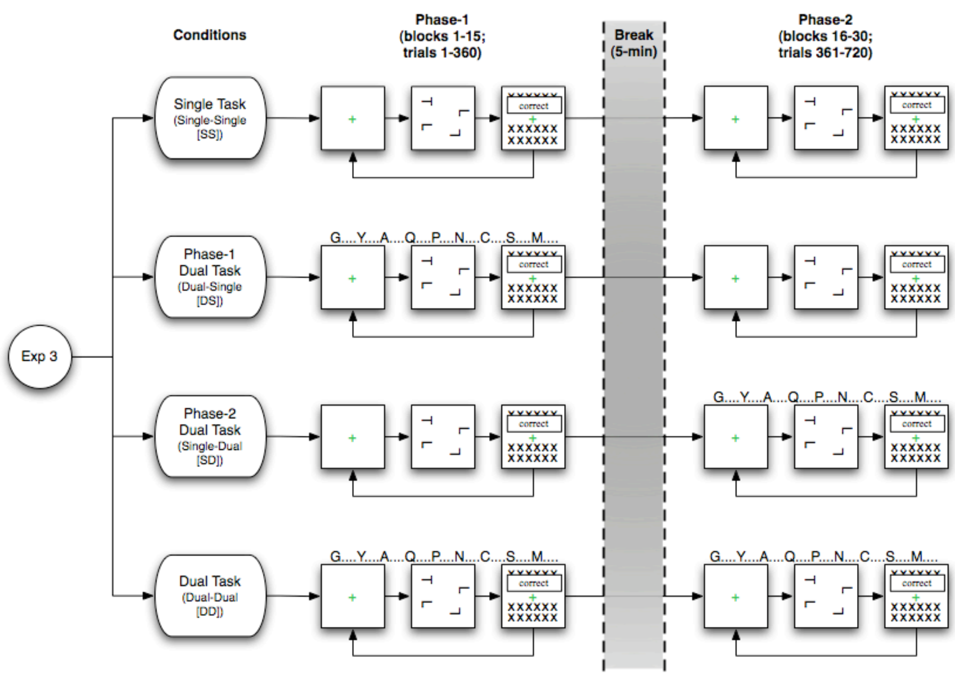

Figure 11. Experiment 3 flow.

As in experiments 1 and 2, there are 2 types of contexts: repeating and unique. Within a block of 24 trials, all contexts differed. There were 12 contexts that were repeated across 30 blocks (i.e., repeating contexts). The other 12 contexts within each block were random (i.e., unique contexts). Hence, participants searched through 360 unique contexts and 12 repeating contexts 30 times, each.

A goal of the current study was to determine if different people scan the same stimulus in a similar manner. Thus, the exact same repeating contexts and target locations were used across participants. In order to ensure that effects are not attributable to luckily using a certain context across all participants, 3 configuration-groups of repeating contexts using the same target locations were used between participants. Target locations were kept constant across repeating and unique contexts to rule out target location differences if there were any configuration group effects.

Cognitive load was manipulated as a between-participant transfer task to uncover effects of increased load on scanning behavior. There were 4 transfer groups: single-single (SS), dual-single (DS), single-dual (SD) and dual-dual (DD). The “single” label refers to the set of blocks when participants only performed the visual search task; the “dual” label refers to the set of blocks when participants performed the search task with an added auditory letter classification task. Consequently, the SS group was closest in similarity to the training phase of experiments 1 and 2, and the “classic” contextual cueing paradigm. The DS and SD groups were transfer groups, which transferred from a searching-only phase to a dual-task phase (searching and auditory tasks), or vice-versa. The SS and DD groups serve as baselines for determining transfer effects on all dependent measures (see Figure 11).

The additional auditory task was a letter classification task. This task has been used to manipulate cognitive load in previous research (Myers & Gray, submitted). Participants were auditorally presented random letters of the alphabet with a four-second interstimulus-interval (ISI). Participants were to indicate whether the current letter (*n*) preceded or followed the prior letter (*n*-1) in the alphabet. Participants were instructed to respond as quickly and accurately as possible, and that if they failed to respond to the alphabet task within the allotted 4 s ISI, the response would be counted as incorrect. The task continued without interruption through all trials when a participant was completing dual-task blocks.

2.3.1.1.2 Experiment 3 Apparatus

2.3.1.1.2.1 Experiment 3 Task Environment

The task environment was built in-house using ANSI common Lisp in the LispWorks development environment. The task environment runs on Apple Macintosh OS 10.4.4.

Each stimulus context contained 12 items, eleven "L" and one "T". Items were oriented in either the 90° or 270° position. Participants responded to the direction of the "T" using a Cedrus® response pad by pressing *right* if the T's top was on the right, and *left* if the top was on the left (see Figure 12). Contexts were presented on a 17" flat-panel display at a resolution of 1280 x 1024. Each item subtended approximately 0.5° of visual angle at a viewing distance of approximately 22 inches. The centers of all items were separated by a minimum of 3° of visual angle. Consequently, the minimum distance between items was 2.5° of visual angle. Due to the size, and the small minimum distance between each item on a trial, information cannot be easily encoded in peripheral vision.

It is important to restate how unique and repeating contexts were created. First, an even number of different target locations was determined. Half of the target locations were for unique contexts, and half were for repeating contexts. (Target locations were used for all participants.) Distractor locations were then added to target locations for repeating contexts, under the condition that the added distractor locations did not come within a specified minimum item-to-item distance (3° of visual angle). Afterward, the same repeating contexts were used across the experiment. Consequently, when it is time to display one of the repeating contexts, a repeating context was randomly selected without replacement from the set of repeating contexts and displayed to the participant. Three groups of repeating contexts were used across all participants, and each group shared the same target locations. Three different sets of repeating contexts were created, called configuration-groups. Participants were then randomly assigned to a configuration group. Thus, within a configuration-group, each participant searched through the same repeating contexts.

When it was time to display a unique context, one of the target locations set aside for unique contexts was randomly selected without replacement. Distractor locations were then added to the target location to create a unique context, under the condition that the items (distractors and targets) did not come within the specified minimum item-to-item distance. Once the sets of unique context target locations and repeating contexts were exhausted, a new block of trials began with the same unique context target locations and the same repeating contexts. Thus, within a configuration-group, each participant searched through the same repeating contexts and the same unique context target locations.

Figure 12. Cedrus response pad configuration for experiment 3.

All stimuli in the letter classification task were presented via Apple's speech software, using its "Victoria" voice, throughout the experiment without interruption. Responses were made using a Cedrus® button box (see Figure 12). Three letters were excluded (E, V, W) due to discrimination difficulty.

2.3.1.1.2.2 Experiment 3 Eye Tracker

The same eye tracker used in experiments 1 and 2 was used in experiment 3.

2.3.1.1.3 Experiment 3 Participants

A total of 62 students from Rensselaer Polytechnic Institute participated in the experiment. A total of 2 hours of experiment credit was provided as compensation to all who completed the task.

2.3.1.1.4 Experiment 3 Procedure

After signing an informed consent form, each participant was randomly assigned to a cognitive load transfer group and configuration-group. Next, each participant was given the appropriate task instructions. Following instructions, each participant was calibrated to the eye tracker.

Next, the participant completed 15 blocks of trials. After completing the first 15 blocks, each participant took a mandatory 5-minute break. After the break the participant began the final 15 blocks of the experiment in the appropriate transfer condition. After completing the final trial, the participant was debriefed and awarded compensation for their time.

2.3.2 Experiment 3 Results

First, results from the letter classification task are presented, followed by trial accuracy results. Next trial response time results are presented. Finally, scan pattern results are presented. The trial accuracy, response time, and scan pattern results begin with an omnibus analysis, and are then separated between workload and transfer results. The section ends with a summary of all results.

2.3.2.1 Experiment 3 Letter Classification Task

Three of the four transfer-load conditions had the letter classification task (DD, DS, and SD). First DD and DS will be compared across the first phase (blocks 1-15), followed by DD and SD across the second phase (blocks 16-30). Finally, DS is compared to SD to see if there are differences between the first phase and second phase from the two different conditions.

A 2 (transfer-load) x 3 (configuration-group) x [2 (context-type) x 15 (block)] mixed ANOVA was conducted on the mean proportion of correct responses, per block, from the DD and DS groups. No outliers were removed. Block violated sphericity, and the Greenhouse-Geisser correction was used. The mean proportion of correct responses for DS was 0.81 and was 0.78 for DD. The main effect of block approached significance [$F(7.92, 189.99) = 1.974$, $p = 0.052$], where participants improved after the first block, and reached asymptote by the second block. No other effects were significant (see Table C1).

A 2 (transfer-load) x 3 (configuration-group) x [2 (context-type) x 15 (block)] mixed ANOVA was conducted on the mean proportion of correct responses, per block, from the DD and SD groups. No outliers were removed. Block violated sphericity, and the Greenhouse-Geisser correction was used. The mean proportion of correct responses for SD was 0.81 and was 0.78 for DD. The main effect of block reached was not significant [$F(8.69, 191.96) = 1.03$, $p > 0.42$]. No other effects were significant (see Table C2).

A 2 (transfer-load) x 3 (configuration-group) x [2 (context-type) x 15 (block)] mixed ANOVA was conducted on the mean proportion of correct responses, per block, from the DS and SD groups for blocks 16-30. No outliers were removed. The mean proportion of correct responses for SD was 0.81 and was 0.81 for DS. The main effect of block reached significance [$F(8.68, 208.36) = 2.12$, $p > 0.031$], where participants improved after the first block, and reached asymptote by the second block. No other effects were significant (see Table C3).

2.3.2.2 Experiment 3 Trial Accuracy Results

A 4(transfer-load) x 3 (configuration-group) x [2(context-type) x 30(block)] mixed ANOVA was conducted to determine if there were systematic differences in trial accuracy attributable to the independent variables used in experiment 3. The dependent variable was the proportion of correct trials. After removing outliers, there were 12 SS participants, 13 SD participants, 15 DS participants and 14 DD participants. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C4).

There was a significant main effect of context-type [$F(1, 42) = 11.14$, $p = 0.002$], where unique contexts resulted in a higher mean proportion of trial responses per block ($M_{Unique} = 0.976$) than repeating contexts ($M_{Repeating} = 0.971$). There was also a significant block x transfer-load interaction [$F(87, 435.68) = 2.19$, $p < 0.001$]. The results demonstrate differences in accuracy by context-type, where unique contexts are responded to more accurately than repeating contexts, though this difference (0.005) seems trivial. The block x transfer-load interaction demonstrates that different levels of load differentially affect trial accuracy with task experience. The next two sections address how workload and transferring from low-load to high-load (and vice-versa) affect trial accuracy.

2.3.2.2.1 Workload Results

Participants performed either the searching and letter classification tasks, or just the searching task within the first phase of experiment 3. To determine how workload affected searching task response accuracy, a 2(load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted on phase-1 data to determine if there were systematic differences in trial accuracy attributable to differences in workload. The dependent variable was the proportion of correct trials. After removing outliers, there were 26 participants in the dual-task group and 29 participants in the single-task group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C5).

There was a main effect of context, [$F(1, 49) = 4.26$, $p = 0.044$], where unique contexts resulted in a higher mean proportion of correct responses per block (M_{Unique} = 0.976) than repeating contexts ($M_{Repeating}$ = 0.971). There was a main effect of block, [$F(5.94, 291.27) = 4.25$, $p < 0.001$], where the first block had a lower mean proportion of trial responses ($M_{block\text{-}1}$ = 0.962) than the 15th ($M_{block\text{-}15}$ = 0.983) block. Finally, there was a main effect of load, [$F(1, 49) = 15.03$, $p < 0.001$], where the single task group (M_{single} = 0.981) had a greater proportion of correct trials than the dual task group (M_{single} = 0.957). Neither the context x load, or the block x load, or the context x block interactions were significant ($p = 0.076$, $p = 0.071$, and $p = 0.916$, respectively). No other effects were significant.

2.3.2.2.2 Training and Transfer Results

To determine how transferring from low-load to high-load conditions, and vice-versa, affect trial accuracy, 4 analyses were performed. The first two analyses are "training equivalency analyses" and were conducted to determine if performance in the same conditions of phase 1, were statistically indistinguishable (i.e., SS compared to SD, and DD compared to DS). Both SS and SD began the experiment in the single task condition, and DD and DS began the experiment in the dual-task condition. Ideally, performance from SS and SD, and from DD and DS, will not be different in phase 1.

The last two analyses were performed to (1) determine what effects were present when participants transferred from low-load to high-load (i.e., phase-2 of SS compared to phase-2 of SD) and (2) determine what effects were present when participants transferred from high- to low-load (i.e., phase-2 of DS compared to phase-2 of SS). If results from the first two analyses demonstrate that SS and SD and DD and DS were equivalent and that the second set of analyses demonstrate that SS and SD and DS and SS differ in the second half of the experiment (phase 2), then there is good evidence of load effects when transferring from low-load to high-load, and vice versa.

2.3.2.2.2.1 Training Analyses

To determine if SS and SD were equivalent, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted on phase-1 data. After removing outliers, there were 12 participants in the SS group and 15 participants in the SD group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used. No effects were significant, showing that SS and SD were equivalent in phase-1 (see Table C6).

To determine if DD and DS were equivalent, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 30(block)] mixed ANOVA was conducted. After removing outliers, there were 15 participants in the DS group and 14 participants in the DD group. Block violated sphericity, and the Greenhouse-Geisser correction was used (see Table C7). There was a main effect of context [$F(1, 23) = 7.198$, $p = 0.013$], where repeating contexts resulted in a greater proportion of correct trials ($M_{Repeating} = 0.961$) than unique contexts ($M_{Unique} = 0.953$). There was also a significant block x configuration-group interaction [$F(10.65, 122.42) = 1.95$, $p = 0.041$], where configuration-group 1 (see Figure 13) did not improve across blocks at the same rate as the other two configuration-groups. Importantly, there was not a main effect of transfer-load [$F(1, 23) = 1.64$, $p > 0.21$], and transfer-load did not interact with context ($p = 0.38$), or with block ($p = 0.062$), or with context x block ($p = 0.092$). No other effects were significant. The results demonstrate the equivalency of DS and DD in phase-1.

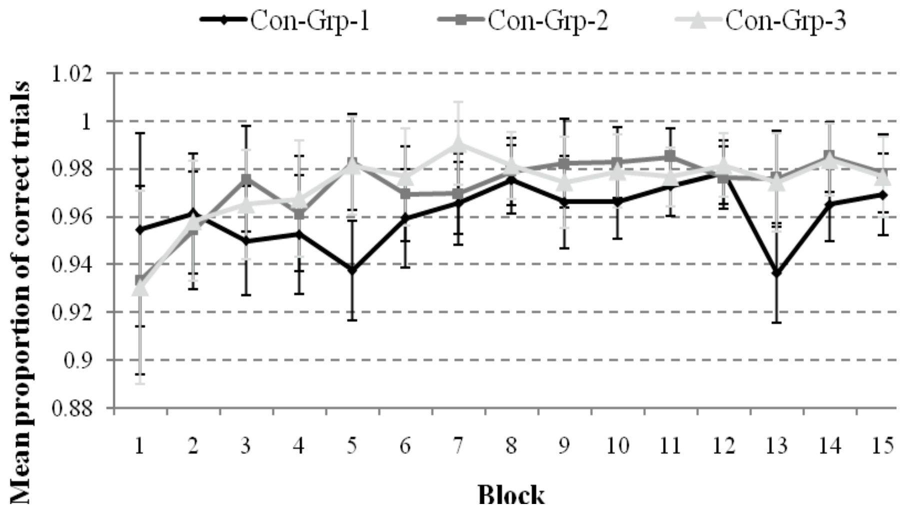

Figure 13. Configuration-group x block interaction on mean proportion of correct trials between dual-dual and dual-single within phase-1. Error bars represent 95% confidence intervals.

2.3.2.2.2.2 Transfer Analyses

To determine if SD and SS differed after being transferred to a dual task scenario or continuing with a single task scenario, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted. After removing outliers, there were 13 participants in the DS group and 13 participants in the DD group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C8). There was a context x configuration-group interaction [$F(1, 20) = 5.53$, $p = 0.012$], where configuration-group 1 did not result in as many accurate responses in the unique contexts as the repeating contexts, while the other 2 configuration groups were equivalent across context-type (see Figure 14). Importantly, there was not a main effect of transfer-condition [$F(1, 20) = 2.79$, $p > 0.11$, *NS*], demonstrating that transferring from a single-task to a dual-task scenario did not affect accuracy results between groups. No other effects were significant.

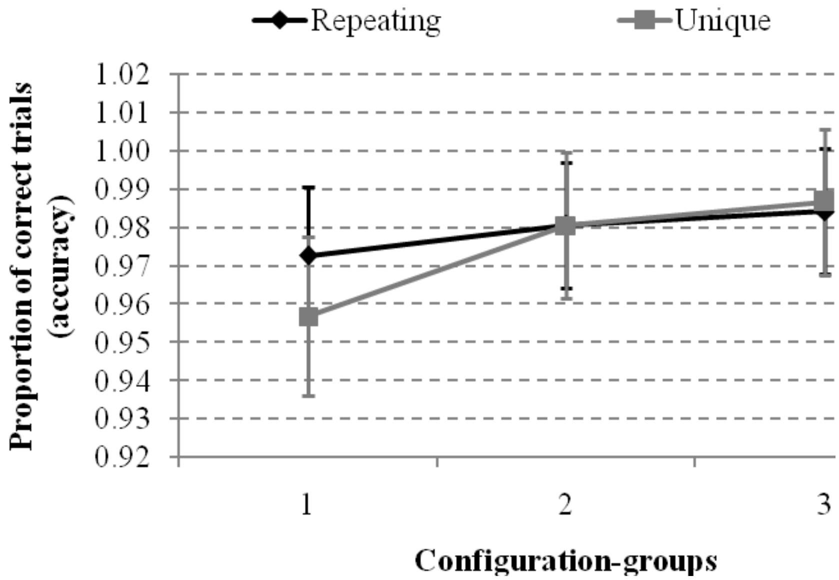

Figure 14. Configuration-group x context-type interaction on the mean proportion of correct trials between single-single and single-dual in phase-1. Error bars represent 95% confidence intervals.

To determine if SS and DS differed after being transferred to a single task scenario from a dual task scenario or a single-task scenario, a 2(transfer-load) x 3(configuration-group) x [2(context-type) x 30(block)] mixed ANOVA was conducted. After removing outliers, there were 13 participants in the DS group and 13 participants in the SS group. Block violated sphericity, and the Greenhouse-Geisser correction was used. Importantly, there was not a main effect of transfer-load [$F(1, 22) = 1.75$, $p > 0.19$, *NS*], nor did transfer load interact with any other independent variable. No other effects were significant (see Table C9).

2.3.2.2.3 Experiment 3 Trial Accuracy Results Summary

A high level of accuracy was maintained across experiment 3, never dropping below 0.90 within a block. Accuracy was affected as a function of transfer-load condition, was improved across blocks, and unique contexts elicited more accurate responses than repeating contexts. Although increased task-load decreased accuracy, transferring from single-task to dual-task, or vice-versa, did not affect accuracy. Interestingly, configuration-group tended to interact with other independent variables (e.g., context-type and block) in dual-task scenarios. It is unclear why increased cognitive load would affect different configuration-groups differently (see figures 13 and 14).

2.3.2.3 Experiment 3 Response Time Results

Response time results will be divided between the omnibus ANOVA, workload effects and transfer effects, just as the accuracy results presented above. A 4(transfer-load) x 3 (configuration-group) x [2(context-type) x 30(block)] mixed ANOVA was conducted to determine if there were systematic differences in mean response times attributable to the independent variables used in experiment 3. After removing outliers, there were 13 SS participants, 14 SD participants, 16 DS participants and 13 DD participants. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used. There was a significant block x transfer-load interaction [$F(11.38, 166.45) = 5.498$, $p < 0.001$], demonstrating that transfer-load conditions differentially affected response times across blocks. Importantly, neither the main effect of context [$F(1, 44) = 0.56$, $p > 0.45$, *NS*], nor the context x block interaction [$F(2.48, 108.89) = 2.35$, $p > 0.085$],were significant. No other effects were significant (see Table C10).

As in experiments 1 and 2, a contextual cueing effect was not established when analyzing the response times as a function of block. Different from experiments 1 and 2, it is possible that the context x block interaction was washed out by including the transfer groups SD and DS. Furthermore, experiment 1 produced a contextual cueing effect after aggregating response times into epochs and only including epochs 1 and 4 in the analyses. To determine if contextual cueing was absent from the omnibus *F* test by including the DS and SD transfer-load groups and not aggregating data into epochs, a 2 (context-type) x 2 (epoch) repeated measures ANOVA was applied to response times from the transfer-load group most similar to experiments 1 and 2–the SS group. There was a significant main effect of epoch [$F(1,11) = 83.91$, $p < 0.001$]. However, neither the main effect of context-type [$F(1,11) = 0.495$, $p > 0.49$, *NS*], nor the context-type by epoch interaction [$F(1,11) = 0.31$, $p > 0.59$, *NS*] were significant. No other effects were significant (see Table C11).

To determine if contextual cueing occurred in the DD transfer-load group, a 2 (context-type) x 2 (epoch) repeated measures ANOVA was applied to response times.

There was a significant main effect of epoch [$F(1, 11) = 37.55$, $p < 0.001$]. However, neither the main effect of context-type [$F(1,11) = 0.392$, $p > 0.54$, *NS*], nor the context-type by epoch interaction [$F(1,11) = 0.35$, $p > 0.56$, *NS*] were significant. No other effects were significant (see Table C12). Just as experiment 2, experiment 3 failed to produce a reliable contextual cueing effect.

2.3.2.3.1 Workload Results

A 2(load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted on phase-1 response times to determine if there were systematic differences attributable to differences in workload. After removing outliers, there were 28 participants in the dual group and 28 participants in the single group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used.

On average, dual-task response times (M_{Dual} = 2490.58 ms) were greater than single-task response times (M_{Single} = 1875.72 ms), and significantly interacted with block [$F(1.69, 84.8) = 4.65$, $p = 0.016$] (see Table C13). Response times from the dual-task condition decreased at a faster rate than response times from the single-task condition (see Figure 15). No other interactions were significant.

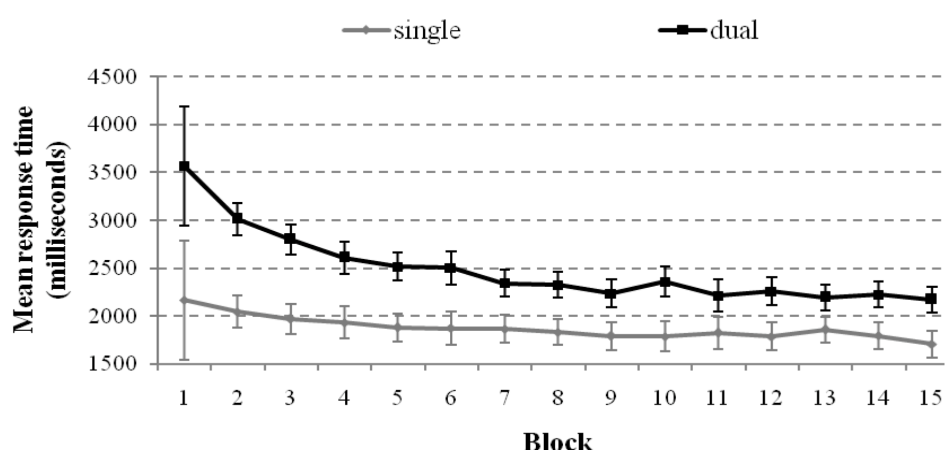

Figure 15. The load x block interaction on response times from phase-1. Error bars represent 95% confidence intervals.

2.3.2.3.2 Training and Transfer Results

Just as the trial accuracy analyses above, the response time analyses are divided between equivalency analyses of phase-1 and phase-2 analyses for determining differences when transferring from low-load to high-load, and vice versa.

2.3.2.3.2.1 Training Analyses

To determine if SS and SD were equivalent in phase-1, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted. After removing outliers, there were 13 participants in the SS group and 14 participants in the SD group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used. There was a main effect of block, [$F(7.57, 158.94) = 12.35$, $p < 0.001$], where response times decreased from the first block to the last block (15th) of phase-1. Importantly, there was not a main effect of transfer-load [$F(1, 21) = 0.019$, $p > 0.89$, *NS*], nor did transfer-load interact with any of the other independent variables (see Table C14).

To determine if DD and DS were equivalent, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted. After removing outliers, there were 14 participants in the DS group and 14 participants in the DD group. Block, and context x block, violated sphericity, and the Greenhouse-Geisser correction was used. There was a main effect of block [$F(1.73, 38.07) = 9.15$, $p = 0.001$]. Importantly, there was not a main effect of transfer-condition [$F(1, 22) = 1.59$, $p > 0.21$], and transfer-condition did not interact with context ($p > 0.83$), or with block ($p > 0.09$), or with context x block ($p > 0.14$). No other effects were significant (see Table C15). The results from the first two analyses demonstrate the equivalency of SS to SD and DS to DD in the first phase of the experiment.

2.3.2.3.2.2 Transfer Analyses

To determine if SD and SS differed after being transferred to a dual task scenario or continuing with a single task scenario, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted. After removing outliers, there were 13 participants in the SD group and 13 participants in the SS group. Block violated sphericity, and the Greenhouse-Geisser correction was used (see Table C16). There was a main effect of transfer-load [$F(1, 20) = 15.30$, $p = 0.001$], demonstrating that transferring from a single-task to a dual-task scenario affected response times between groups. No other effects were significant.

To determine if SS and DS differed after being transferred to a single task scenario or continuing with a dual task scenario, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted. After removing outliers, there were 15 participants in the DS group and 13 participants in the SS group. Block violated sphericity, and the Greenhouse-Geisser correction was used. Importantly, there was not a main effect of transfer-load [$F(1, 22) = 1.2$, $p > 0.28$, *NS*], nor did transfer-load interact with any other independent variable. No other effects were significant (see Table C17).

2.3.2.3.3 Experiment 3 Response Time Results Summary

Experiment 3 failed to produce a reliable contextual cueing effect. Dual-task conditions produced longer response times than single-task conditions. Not surprisingly, transferring from a single-task to a dual-task caused an increase in response times, and transferring from a dual-task to a single-task caused a reduction in response times.

2.3.2.4 Experiment 3 Scan Pattern Results

As in experiments 1 and 2, ProtoMatch software (Myers & Schoelles, 2005) was used to calculate dwells, determine the items associated with each dwell, and calculate dependent measures associated with dwells and associated objects such as dwell durations. To determine if visual scans were refined across repeated searches through repeating contexts, NSIs were computed for each type of context for each participant. There were 30 analyzable blocks of 24 trials (6 epochs) in experiment 3. The following analyses are directed toward determining if all FAST criteria are present in experiment 3. The section is divided into FAST's criteria, where the omnibus analysis, workload, and transfer results are reported.

2.3.2.4.1 Criterion 1: Dwell Reduction across Repeated Search

The number of dwells and re-dwells was reduced across training-phase blocks of experiment 1 and 2. First, the results from analyses on the number of dwells to find the target are presented and followed by the same analyses for the number of re-dwells.

2.3.2.4.1.1 Dwell Analyses

If FAST's first criterion of scan refinement occurred in experiment 3, the number of dwells to find a target should be reduced across blocks of trials. A 4(transfer-load) x 3(configuration-group) x [2(context-type) x 20(block)] mixed ANOVA was performed on all dwells on stimulus items. After removing outliers, there were 14 DD participants, 14 DS participants, 12 SD participants, and 12 SS participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used (see Table C18). There was a significant block x transfer-load interaction [$F(23.58, 314.45) = 3.06$, $p < 0.001$], where the number of dwells to find the target was reduced as a function of experience and cognitive load (see Figure 16). No other effects were significant.

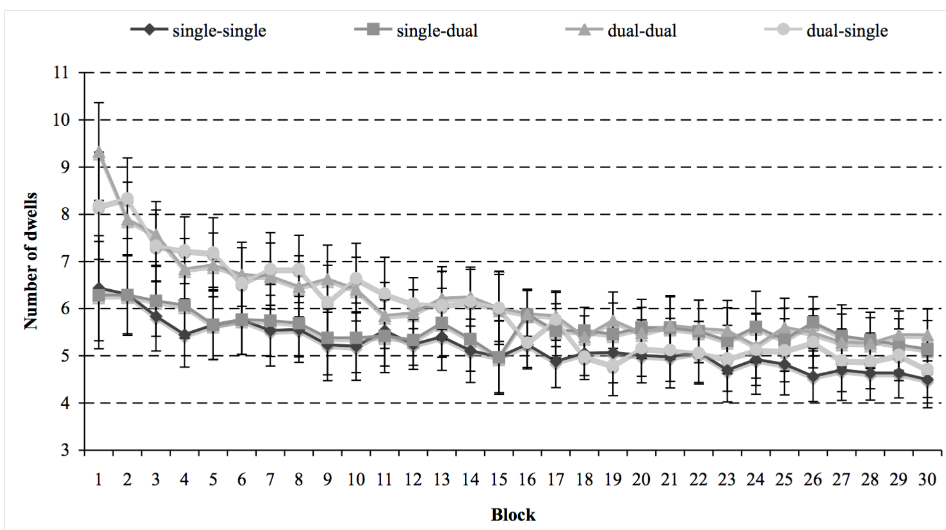

Figure 16. Block by transfer-load interaction on the number of dwells within a trial. Error bars represent 95% confidence intervals.

i) Workload Effects

To determine how workload affected the number of dwells to find the target, a 2(load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted on the number of dwells from the first 15 blocks (phase 1). The dependent variable was the number of dwells to find the target. After outliers were removed, there were 24 single-task participants and 28 dual-task participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C19). There was a block x load interaction, where participants in the dual-task conditions in phase-1 (DD and DS) reduced the number of dwells to find the target at a faster rate than participants in the single-task condition in phase-1 (SS and SD) (see Figure 16, blocks 1-15). This result shows number of dwells to find a target are reduced with experience, and at a greater rate in dual-task conditions. Moreover, there was also a context x block interaction [$F(8.98, 413.13) = 3.97$, $p = 0.008$], where the number of dwells to find the target were reduced across blocks in repeating contexts at a faster rate than in unique contexts. Finally, there was also a significant context x transfer-load x configuration-group interaction [$F(2, 46) = 4.34$, $p = 0.019$], where the number of dwells to find a target was greatest in repeating contexts from configuration-group 2 in the dual-task conditions of phase-1 (see Figure 17).

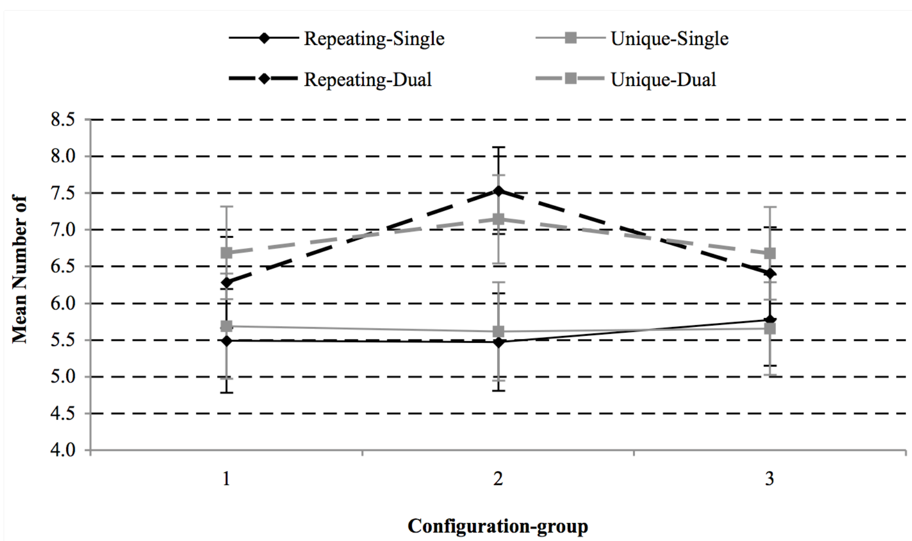

Figure 17. The load x configuration-group x context interaction. Error bars represent 95% confidence intervals.

ii) Training and Transfer Effects

First equivalency analyses are conducted between SS and SD (and DS and DD) to ensure that the number of dwells to find the target were equivalent before being transferred into either a dual- or single-task scenario.

a. Training Results

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted to ensure that the SS and SD groups behaved equivalently in phase-1. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. Neither block, nor the context-type x block interaction, violated sphericity, thus no corrections were used. Importantly, the main effect of transfer-load was not significant [$F(1, 18) = 0.296$, $p > 0.59$, *NS*], nor did it interact with any of the other independent variables (see Table C20). There was a significant effect of block [$F(5.395, 97.12) = 6.79$, $p < 0.001$], where the number of dwells was significantly reduced across blocks.

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted to ensure that the DS and DD groups behaved equivalently in phase-1. After removing outliers, there were 14 DS participants and 14 DD participants; or, 9 participants from configuration group 1, 10 from group 2, and 9 participants from group 3. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C21). Importantly, the main effect of transfer-load was not significant [$F(1, 22) = 0.001$, $p > 0.97$, *NS*], nor did it interact with any of the other independent variables. There was a significant context-type x block interaction [$F(6.87, 151.2) = 2.3$, $p = 0.03$], where the number of dwells was significantly reduced across blocks at a greater rate in repeating contexts than in unique contexts. Finally, there was a significant context-type x configuration-group interaction [$F(2, 22) = 5.29$, $p = 0.013$], where configuration-group 2 affected the number of dwells to find the target differently than the other two configuration-groups (see Figure 18).

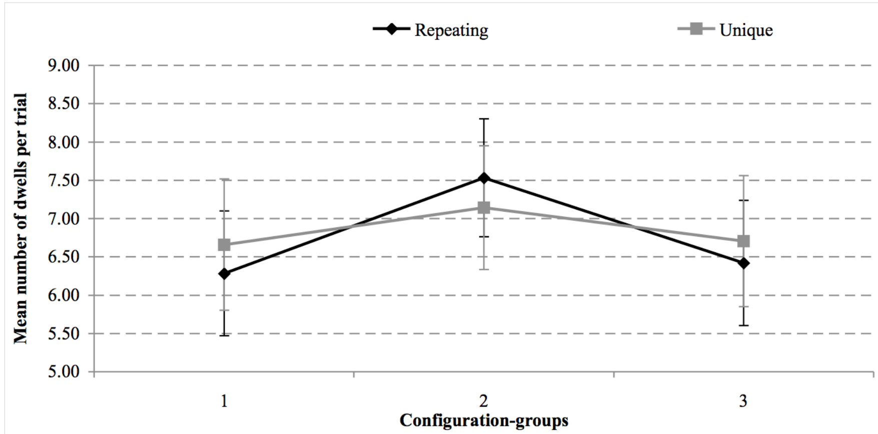

Figure 18. Context x configuration-group interaction in phase-1 dual-dual and dual-single transfer-load conditions from phase-1. Error bars represent 95% confidence intervals.

b. *Transfer Results*

To determine if transferring from a single-task to the dual-task affected the number of dwells to find the target, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and SD groups. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. The context-type x block interaction violated sphericity, thus Greenhouse-Geisser correction was used. Importantly, the main effect of transfer-load was not significant [$F(1, 18) = 0.296$, $p > 0.59$, *NS*], nor did it interact with any of the other independent variables (see Table C22). There was a significant main effect of block [$F(14, 252) = 1.799$, $p = 0.039$], where the number of dwells was significantly reduced across blocks. Interestingly, and unexpectedly, there was not a difference in the mean number of dwells between the SD ($M = 5.5$) and SS ($M = 4.9$) in phase-2 [$F(1, 18) = 3.57$, $p > 0.074$, *NS*].

Finally, to determine if transferring from a dual-task to the single-task affected the number of dwells to find the target, 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and DS groups (see Table C23). After removing outliers, there were 14 DS participants and 12 SS participants; or, 9 participants from configuration group 1, 9 from group 2, and 8 participants from group 3. Importantly, the main effect of transfer-load was not significant [$F(1, 22) = 0.001$, $p > 0.97$, *NS*], nor did it interact with any of the other independent variables. There was a significant main effect of block [$F(14, 280) = 2.37$, $p = 0.004$], where the number of dwells was significantly reduced across blocks. Interestingly, and unexpectedly, there was not a difference in the mean number of dwells between the DS ($M = 5.1$) and SS ($M = 4.9$) in phase-2 [$F(1, 20) = 0.641$, $p > 0.43$, *NS*].

2.3.2.4.1.2 Re-dwell Analyses

Further evidence that FAST's first criterion of scan refinement occurred in experiment 3 can be provided by reductions in re-dwells, as in experiments 1 and 2. A 4(transfer-load) x 3(configuration-group) x [2(context-type) x 20(block)] mixed ANOVA was performed on all re-dwells (two, or more, dwells assigned to the same display item within a trial). After removing outliers, there were 14 DD participants, 14 DS participants, 12 SD participants, and 12 SS participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3. Block, and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used (see Table C24).

There was a significant block x transfer-load interaction [$F(21.08, 281.09) = 3.93$, $p < 0.001$], where the mean number of re-dwells within a trial was reduced as a function of experience and cognitive load (see Figure 19).

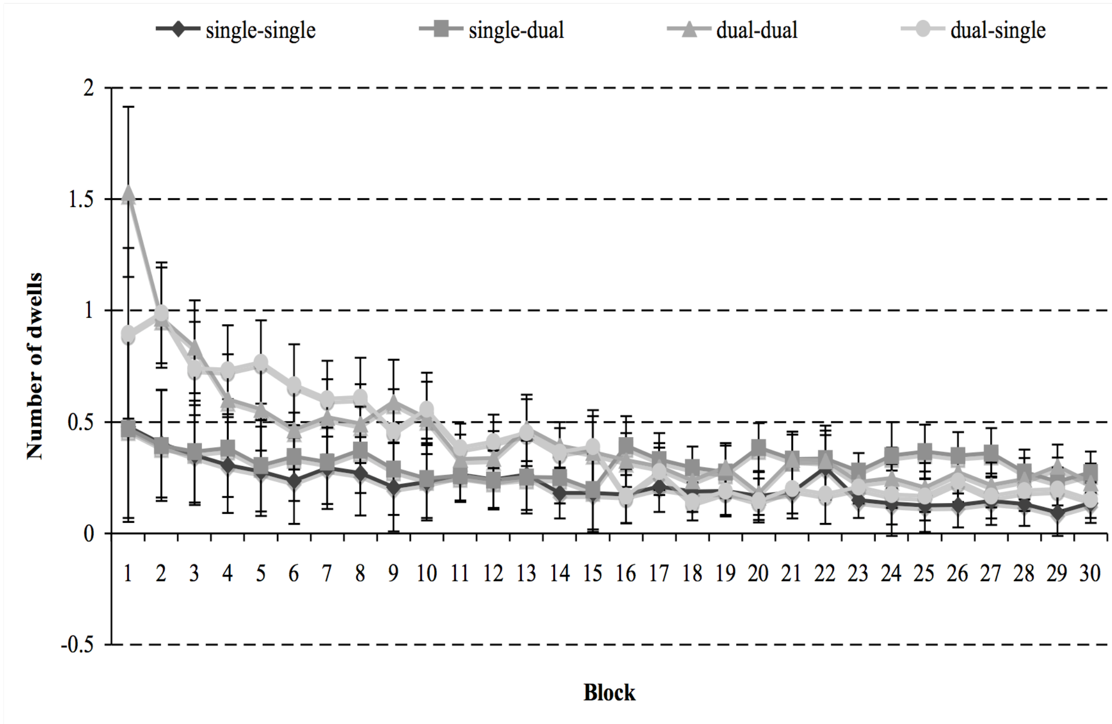

Figure 19. Block by transfer-load interaction on the mean number of re-dwells per block of trials. Error bars represent 95% confidence intervals.

iii) Workload Effects

To determine how workload affected the number of dwells to find the target, a 2(load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed ANOVA was conducted on the number of dwells from the first 15 blocks (phase 1). The dependent variable was the number of dwells to find the target. After removing outliers, there were 24 single-task participants and 28 dual-task participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C25). Importantly, there was a block x load interaction [$F(4.79, 220.49) = 4.71$, $p = 0.001$], where participants in the dual-task conditions in phase-1 (DD and DS) reduced the number of re-dwells to find the target at a faster rate than participants in the single-task condition in phase-1 (SS and SD) (see Figure 19, blocks 1-15). This result demonstrates that number of re-dwells to find a target is reduced with experience, and at a greater rate in dual-task conditions. There was also a significant context x block x configuration-group interaction [$F(13.42, 308.62) = 1.75$, $p = 0.048$].

iv) Training and Transfer Effects

First equivalency analyses are conducted between SS and SD (and DS and DD) to ensure that the number of dwells to find the target were equivalent before being transferred into either a dual- or single-task scenario.

a. Training Results

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted to ensure that the SS and SD groups behaved equivalently before moving on to phase-2 of the experiment. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. Block violated sphericity, thus the Greenhouse-Geisser correction was used. Importantly, the main effect of transfer-load was not significant [$F(1, 18) = 0.725$, $p > 0.40$, *NS*], nor did it interact with any of the other independent variables (see Table C26). There was a significant effect of block [$F(6.07, 109.19) = 5.21$, $p < 0.001$], where the number of re-dwells was significantly reduced across blocks.

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted to ensure that the DS and DD groups behaved equivalently before moving on to phase-2 of the experiment. After removing outliers, there were 14 DS participants and 14 DD participants; or, 9 participants from configuration group 1, 10 from group 2, and 9 participants from group 3. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used. Importantly, the main effect of transfer-load was not significant [$F(1, 22) = 0.001$, $p > 0.97$, *NS*], nor did it interact with any of the other independent variables (see Table C27). There was a significant main effect of block [$F(4.27, 93.97) = 12.11$, $p < 0.001$], where the number of dwells was significantly reduced across blocks.

b. Transfer Results

To determine if transferring from a single-task to the dual-task affected the number of dwells to find the target, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and SD groups. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. Block, and the context-type x block interaction, violated sphericity, thus Greenhouse-Geisser correction was used. Interestingly, and different from the dwell analysis, there was a significant main effect of transfer-condition [$F(1, 18) = 7.35$, $p < 0.014$]. Moreover, transfer-condition interacted with configuration-group [$F(2, 18) = 3.57$, $p = 0.049$], where configuration-group 2 resulted in more re-dwells in the SD group than in the SS group during phase-2 of the experiment (see Table C28 and Figure 20). There was a significant main effect of context-type [$F(1, 18) = 8.357$, $p = 0.010$], where repeating contexts ($M = 0.22$) had fewer re-dwells than unique contexts ($M = 0.27$).

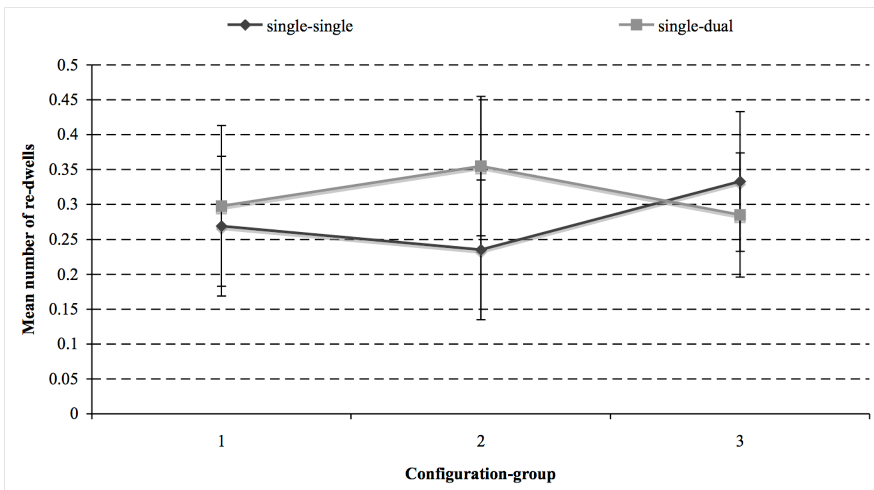

Figure 20. The configuration-group x transfer-load interaction from single-dual and single-single phase-2 re-dwells. Error bars represent 95% confidence intervals.

Finally, to determine if transferring from a dual-task to the single-task affected the number of dwells to find the target, 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and DS groups (see Table C29). After removing outliers, there were 14 DS participants and 12 SS participants; or, 9 participants from configuration group 1, 9 from group 2, and 8 participants from group 3. Importantly, the main effect of transfer-load was not significant [$F(1, 22) = 0.001$, $p > 0.97$, *NS*], nor did it interact with any of the other independent variables. Interestingly, and unexpectedly, there was not a difference in the mean number of re-dwells between the DS and SS in phase-2 [$F(1, 20) = 0.641$, $p > 0.43$, *NS*].

2.3.2.4.1.3 Criterion 1 Summary

First, workload affected dwells and re-dwells similarly. For both, block and load interacted, where dwells and re-dwells in the dual-task groups of phase-1 were reduced at a faster rate than from the single-task group. Surprisingly, configuration-group 2 seemed to affect dwells and re-dwells in a different manner than the other configuration-groups. This was unexpected and it is unclear what was special about configuration-group 2.

Second, phase-1 load equivalency analyses produced no differences between SS and SD or differences between DS and DD. Consequently, behavior from phase-1 SS and SD (i.e., single-task) was equivalent. The same conclusion can also be drawn for the DS and DD groups. Because the equivalency analyses did not produce differences between the groups, any differences between the SS and SD groups and the SS and DS groups from phase-2 would be attributable to transferring from dual-task to single-task, or vice versa.

Finally, the transfer analyses revealed that dwells continued reduction across block, regardless of being transferred from dual-task to single-task or single-task to dual-task. Re-dwells continued reduction when transferring from single-task to dual-task, but did not continue when transferring from dual-task to single-task. Furthermore, unique contexts received more re-dwells than repeating contexts after transferring from a single-task to a dual-task. Furthermore, transfer condition interacted with configuration-group on re-dwells when transferring from a single-task to a dual task, but did not interact when transferring from a dual-task to a single task.

From the analyses, criterion 1 of FAST is supported–both dwells and re-dwells were reduced across blocks during the first phase of the experiment, and dwells continued reduction through the second phase of the experiment. Furthermore, increased cognitive load affects visual scans by increasing the number of dwells and re-dwells to be eventually reduced with experience.

2.3.2.4.2 Criteria 2 & 3: Scan Pattern Similarity Increases Independent of Dwell Reduction & Patterns from Repeating Contexts Increase at a Faster Rate than Patterns from Unique Contexts

Visual scan analyses were conducted to determine if FAST criteria 2 and 3 were present in experiment 3. The NSI metric, used in experiments 1 and 2, was used for computing similarity. If the second criterion is present, then there should be a significant main effect of epoch on NSIs. If the third criterion is present, then there should be a significant context-type x epoch interaction where repeating contexts increase in similarity at a faster rate across epochs than unique contexts. Only dwells that were assigned a stimulus display item were used in the NSI calculation. First, the omnibus ANOVA is reported, and is followed by workload and transfer analyses.

To determine if there were differences in NSIs as a function of transfer-load, configuration-group, context-type or epoch, a 4(transfer-load) x 3(configuration-group) x [2(context-type) x 6(epoch)] mixed ANOVA was performed on all mean NSIs (see Table C30). After removing outliers, there were 14 DD participants, 14 DS participants, 12 SD participants, and 12 SS participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3, resulting in approximately 37,440 visual scans were included in the analyses. Epoch violated the sphericity assumption, and associated results are reported using the Greenhouse-Geisser correction. There was a main effect of context-type [$F(1, 40) = 266.52$; $p < 0.001$] where repeating contexts ($M_{Repeating} = 0.41$) were significantly more similar than unique contexts ($M_{Unique} = 0.39$). There was a main effect of epoch [$F(3.47, 138.69) = 48.22$; $p < 0.001$] demonstrating an increase in similarity across epochs. Importantly, there was a reliable epoch by configuration-type interaction [$F(5, 200) = 7.78$; $p < 0.001$] demonstrating that repeating contexts increased in similarity across epochs at a faster rate than unique contexts (see Figure 21).

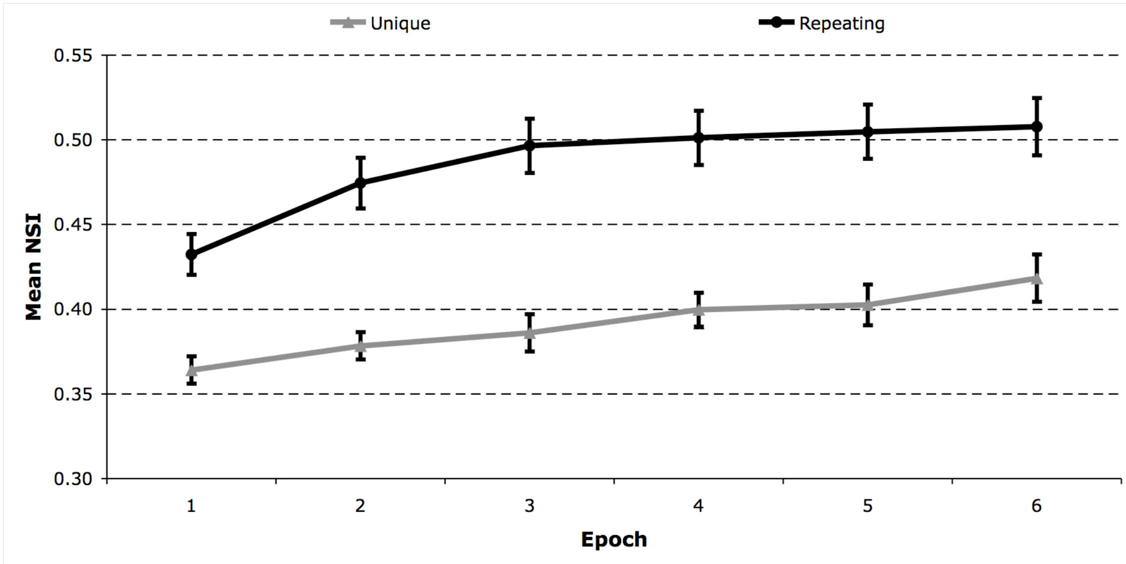

Figure 21. The epoch x configuration-type interaction on NSIs from experiment 3. Error bars represent 95% confidence interval.

There was also a reliable main effect of transfer-condition (SS, SD, DS, DD) [$F(3, 40) = 4.561$; $p = 0.008$]. Planned pairwise comparisons revealed that the SS group's mean NSI was significantly higher than the DS or DD mean NSIs (see Figure 22). These results demonstrate that a dual task situation affects the repeatability of scan patterns, even when the added task is auditory.

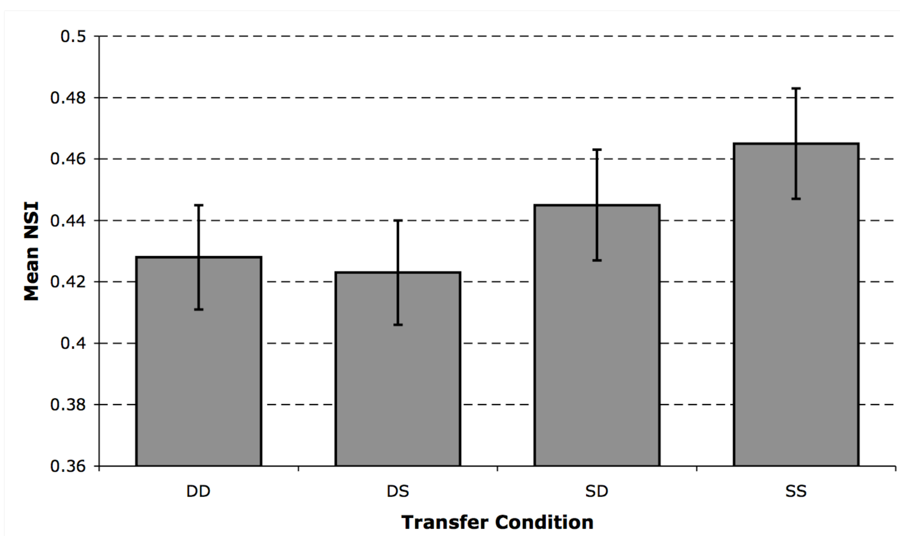

Figure 22. Main effects of transfer-load conditions on NSIs from experiment 3. Error bars represent 95% confidence interval.

2.3.2.4.2.1 Workload Effects

To determine how workload affected scanning similarity, a 2(load) x 3(configuration-group) x [2(context-type) x 3(epoch)] mixed ANOVA was conducted on NSIs from phase-1 (epochs 1-3). After removing outliers, there were 24 single-task participants and 28 dual-task participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3. Epoch violated sphericity, and the Greenhouse-Geisser correction was used (see Table C31). There was a significant 4-way context-type x epoch x load x configuration-group interaction [$F(4, 92) = 2.64$; $p = 0.039$] (see Figure 23). This result indicates that context-types change differentially across epochs within each configuration-group and is differentially affected by the level of cognitive load.

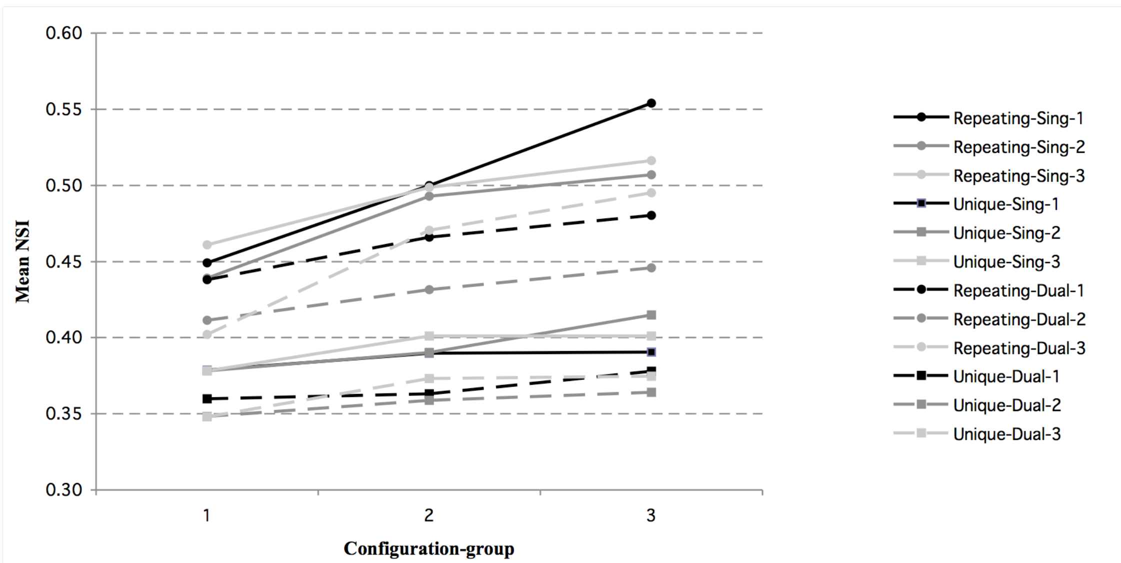

Figure 23. The context-type x epoch x load x configuration group interaction on normalized similarity scores from experiment 3. Error bars were omitted for clarity.

2.3.2.4.2.2 Training and Transfer Effects

First equivalency analyses were conducted between SS and SD (and DS and DD) to ensure that the number of dwells to find the target were equivalent before being transferred into either a dual- or single-task scenario.

i) Training Results

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 3(epoch)] mixed analysis of variance was conducted to ensure that the SS and SD groups behaved equivalently before moving on to phase-2 of the experiment. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. Importantly, the main effect of transfer-load was not significant [$F(1, 18) = 0.47$, $p > 0.5$, *NS*], nor did it interact with any of the other independent variables (see Table C32). There was a significant context-type x epoch interaction [$F(2, 36) = 10.15$, $p < 0.001$], where scan patterns from repeating contexts increased in similarity at a faster rate across epochs than scan patterns from unique contexts.

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 3(epoch)] mixed analysis of variance was conducted to ensure that the DS and DD groups behaved equivalently before moving on to phase-2 of the experiment. After removing outliers, there were 14 DS participants and 14 DD participants; or, 9 participants from configuration group 1, 10 from group 2, and 9 participants from group 3. Epoch violated sphericity, and the Greenhouse-Geisser correction was used. Again, the main effect of transfer-load was not significant [$F(1, 22) = 0.64$, $p > 0.43$, *NS*], nor did it interact with any of the other independent variables (see Table C33). There was a significant context-type x epoch interaction [$F(2, 44) = 7.92$, $p = 0.001$], where scan patterns from repeating contexts increased in similarity across blocks at a faster rate than scan patterns from unique contexts.

ii) Transfer Results

To determine if transferring from a single-task to the dual-task affected scan pattern similarity, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 3(epoch)] mixed analysis of variance was conducted on phase-2 data from the SS and SD groups. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. Epoch violated sphericity, thus Greenhouse-Geisser correction was used. There was not a significant main effect of transfer-condition [$F(1, 18) = 3.22$, $p = 0.09$, *NS*]. There was a main effect of context-type [$F(1, 18) = 76.56$, $p < 0.001$], where repeating contexts were more similar on average than unique contexts. No other effects were significant (see Table C34).

Finally, to determine if transferring from a dual-task to the single-task affected scan pattern similarity, 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and DS groups (see Table C35). After removing outliers, there were 14 DS participants and 12 SS participants; or, 9 participants from configuration group 1, 9 from group 2, and 8 participants from group 3. Interestingly, there was a main effect of scan pattern similarity between the DS and SS in phase-2 [$F(1, 20) = 8.49$, $p = 0.009$], where scan patterns from the SS group ($M_{SS} = 0.48$) were more similar than from the DS group ($M_{DS} = 0.44$).

2.3.2.4.2.3 Criteria 2 & 3 Summary

FAST criteria 2 and 3 were supported with data from experiment 3. The second criterion of FAST, scan pattern similarity increases independent of dwell reduction, was supported by the omnibus ANOVA (see Figure 21), the workload ANOVA, and each of the condition equivalency ANOVAs. Importantly, the third criterion, scan pattern similarity increases at a faster rate in repeating contexts than in unique contexts, was supported in experiment 3 while being absent from experiments 1 and 2.

Increased cognitive load in dual-task groups reduced the similarity of scan patterns (see Figure 22). Interestingly, when transferring from a dual-task scenario to a single-task scenario (DS), scan pattern similarity within the single-task scenario does not reach the same degree of similarity if one were to have started and finished the experiment in a single-task scenario (SS). Furthermore, scan pattern similarity was no different after being transferred to a dual-task scenario and having started in a single-task scenario (SD) when compared to having started and finished the experiment in a single-task scenario (SS). Together, these results suggest that scan patterns are not affected by increased cognitive load after they are acquired, but are disrupted with increased load (though not completely) during their acquisition.

Of particular interest was determining if different configuration-groups resulted in different degrees of scan pattern similarity. Although configuration-group interacted with context-type, epoch, and load in the workload analyses, it did not interact with any other independent variable in any of the other analyses. This suggests that conditions must be just right for different configuration-groups to affect scan pattern similarities.

2.3.2.5 Experiment 3 Dwell Duration Analyses

Although FAST does not claim that dwell durations should change with experience in a task environment, dwell durations were analyzed for completeness. A 4(transfer-load) x 3(configuration-group) x [2(context-type) x 30(block)] mixed ANOVA was performed on all dwells (both assigned to display items, and those unassigned to display items were included). After removing outliers, there were 14 DD participants, 14 DS participants, 12 SD participants, and 12 SS participants; or, 16 participants from configuration group 1, and 18 from groups 2 and 3. Block and the context-type x block interaction violated sphericity, thus the Greenhouse-Geisser correction was used (see Table C36). There was a significant main effect of context-type [$F(1, 40) = 9.86$, $p = 0.003$], where unique contexts resulted in shorter mean dwell durations ($M_{Unique} = 257.6$) than repeating contexts ($M_{Repeating} = 264.3$). There was also a significant block x transfer-load interaction [$F(21.24, 283.15) = 5.84$, $p < 0.001$] (see Figure 24).

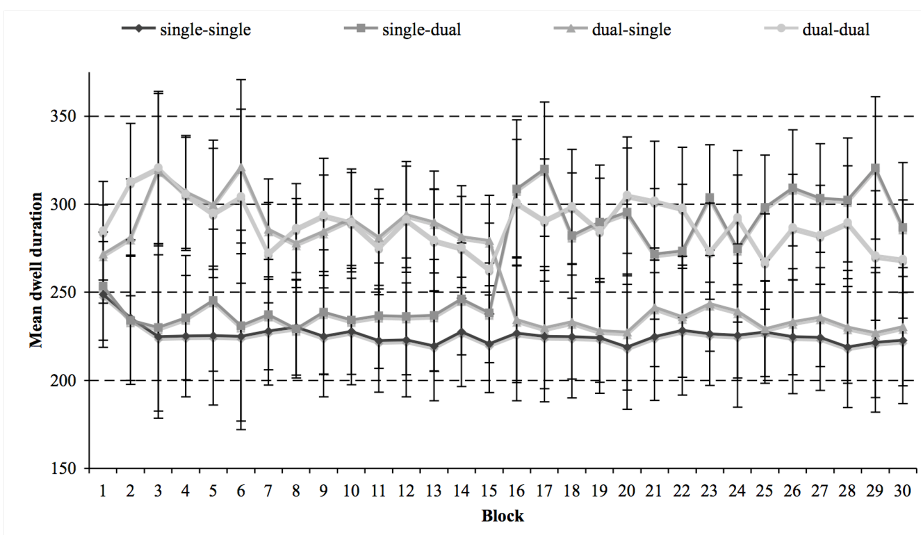

Figure 24. The block x transfer-load interaction on dwell durations from experiment 3. Error bars represent 95% confidence intervals.

2.3.2.5.1 Dwell Duration Workload Effects

A 2(load) x 3 (configuration-group) x [2(context-type) x 30(block)] mixed ANOVA was conducted to determine if there were systematic differences in mean dwell durations that are attributable to differences in workload. After removing outliers, there were 28 participants in the dual group and 24 participants in the single group. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C37).

The main effect of context-type approached significance [$F(1, 46) = 5.84$, $p = 0.053$], where unique contexts resulted in lesser mean dwell durations ($M_{Unique} = 260.41$) than repeating contexts ($M_{Repeating} = 264.8$). There was also a block x load interaction [$F(5.4, 248.55) = 2.84$, $p = 0.014$], where dwell durations in the dual-task were reduced at a slower rate than dwell durations in the single-task.

2.3.2.5.2 Dwell Duration Training and Transfer Effects

First equivalency analyses are conducted between SS and SD (and DS and DD) to ensure that dwell durations were equivalent before being transferred into either a dual- or single-task scenario.

2.3.2.5.2.1 Training Results

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted to ensure that the SS and SD groups behaved equivalently before moving on to phase-2 of the experiment. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group 3. Block violated sphericity, thus the Greenhouse-Geisser correction was used. Importantly, the main effect of transfer-load was not significant [$F(1, 18) = 0.70$, $p > 0.41$, *NS*], nor did it interact with any of the other independent variables (see Table C38). The context x block interaction approached significance [$F(14, 252) = 1.70$, $p = 0.056$] (see Figure 25).

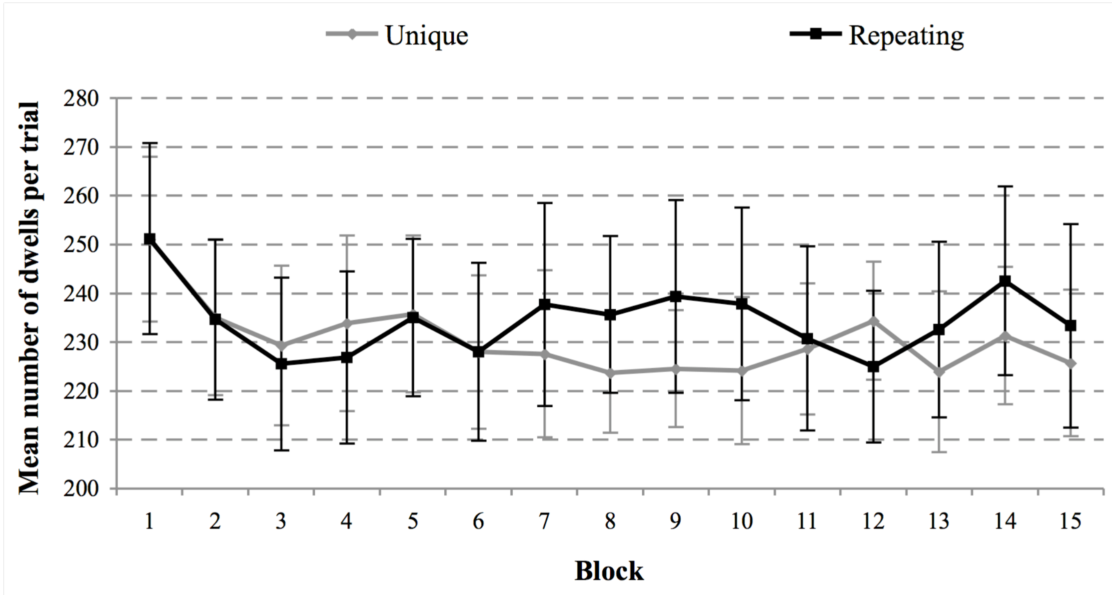

Figure 25. The single-task context x block interaction on dwell durations when aggregating dwell durations into high and low load of experiment 3 phase-1. Error bars represent 95% confidence intervals.

A 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted to ensure that the DS and DD groups behaved equivalently before moving on to phase-2 of the experiment. After removing outliers, there were 14 DS participants and 14 DD participants; or, 9 participants from configuration group 1, 10 from group 2, and 9 participants from group 3. Block, and the context-type x block interaction, violated sphericity, and the Greenhouse-Geisser correction was used (see Table C39). Importantly, the main effect of transfer-load was not significant [$F(1, 22) = 0.002$, $p > 0.96$, *NS*], nor did it interact with any of the other independent variables. There was a significant main effect of block [$F(4.85, 106.69) = 2.39$, $p = 0.045$], where dwell durations were reduced across the blocks of phase-1.

2.3.2.5.2.2 Transfer Results

To determine if transferring from a single-task to the dual-task affected dwell durations, a 2(transfer-load) x 3 (configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and SD groups. After removing outliers, there were 12 SS participants and 12 SD participants; or, 7 participants from configuration group 1, 8 from group 2, and 9 participants from group

3. Block, and the context-type x block interaction, violated sphericity, thus the Greenhouse-Geisser correction was used. The main effect of transfer-load was significant [$F(1, 18) = 16.97$, $p = 0.001$], where the SS group had shorter mean dwell durations ($M_{SS} = 224.35$) than the SD group ($M_{SD} = 296.1$) during phase-2. Transfer-load did not interact with any other independent variables (see Table C40). There was also a significant main effect of context [$F(1, 18) = 9.98$, $p = 0.005$], where mean dwell durations were significantly greater in repeating contexts ($M_{Repeating} = 268.1$) than in unique contexts ($M_{Unique} = 252.3$).

Finally, to determine if transferring from the dual-task to the single-task affected the dwell durations, a 2(transfer-load) x 3(configuration-group) x [2(context-type) x 15(block)] mixed analysis of variance was conducted on phase-2 data from the SS and DS groups (see Table C41). After removing outliers, there were 14 DS participants and 12 SS participants; or, 9 participants from configuration group 1, 9 from group 2, and 8 participants from group 3. The main effect of transfer-load was not significant [$F(1, 20) = 0.44$, $p > 0.51$, *NS*]. However, there was a significant context-type x transfer-load interaction [$F(1, 20) = 5.62$, $p = 0.028$], where dwell durations from repeating contexts were equivalent across SS and DS conditions and dwell durations from unique contexts were less in SS than in DS (See Figure 26).

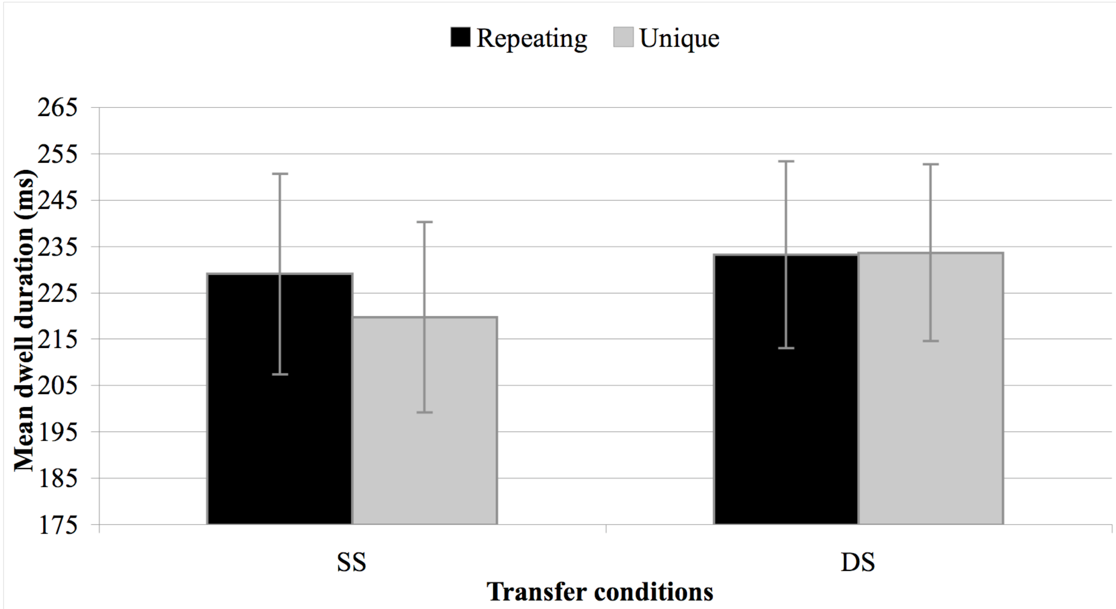

Figure 26. The context-type x transfer-load interaction between single-single and dual-single in phase-2 of experiment 3. Error bars represent 95% confidence interval.

2.3.2.6 Qualifying Influences of Repeating Scan Patterns

There are two extremes of statistical influences on goal-oriented behavior that were discussed earlier, exogenous and endogenous influences. Between these extremes are non-deliberate behaviors that serve a goal and appear strategic. The two extremes and the area between them (see Figure 1) are useful for predictions of scanning refinement.

Scans that result from purely endogenous influences would not be refined. After completing a goal by scanning a stimulus for the first time, all subsequent scan patterns in service of the same goal on the same stimulus would be identical to the first scan pattern. Consequently, scan patterns would repeat perfectly within individuals, but likely be different across individuals. Although this seems very unlikely and a “straw man”, this is precisely what is predicted by scanpath theory (Chernyak & Stark, 2001; Noton & Stark, 1971a, 1971b; Stark & Ellis, 1981; Stark et al., 1980). Indeed, repeating scans were not repeated identically across multiple views of the same stimulus, and instead increased in similarity with experience across all three experiments (see Figures 7, 10, and 21).

Behavior from purely exogenous influences would not be refined, either. The same stimulus would always influence scan patterns in the same manner, leading to repeating scan patterns. Again, repeating scans were not repeated identically across multiple views of the same stimulus, and instead increased in similarity with experience across all three experiments. It is unknown if exogenous influences differ across individuals. If exogenous influences are assumed to be like reflexes (and similar across individuals) then repeating scan patterns on the same stimulus should be similar across individuals.

The extreme influences are clearly difficult to distinguish between with observable behavior. Indeed, experiments 1 and 2 show that neither extreme influence (endogenous or exogenous) is ever the sole influence of scan patterns. Rather, it is more likely that behavior results from influences falling somewhere between these extremes. Learning is assumed to be absent in both extremes. Endogenous influences may occur after learning had ceased such as a settled on and deliberate strategy, while purely exogenous influences are mostly void of learning. Although it would be difficult to differentiate between endogenous and exogenous influences, it is possible determine differences between statistical and endogenous influences, and statistical and exogenous influences. This is because effects of statistical influences are valuable to the process associated to learning and adaptation (Blessing & Anderson, 1996; Gray, Sims, Fu, & Schoelles, 2006; Haider & Frensch, 1999). As experience with a task environment and a paired goal increase, influences may shift from what appear to be exogenous influences to what appear to be to be endogenous influences, though may never become a deliberate or consciously executed strategy.

It is possible to determine if visual scan refinement across epochs is solely a function of the visual stimulus. If repeating scan patterns result from only exogenous influences, and if exogenous influences are the same across individuals (like reflexes), then between-participant NSIs will be identical to the within-participant NSIs, To determine between-participant NSIs, visual scans from participants searching through the same repeating contexts were compared at each block for each of the 12 repeating contexts, as well as for unique context target locations. For example, participant-1's context-A scan pattern was compared to participant-2's context-A scan pattern, and then to participant-3's context-A scan pattern etc. Next, mean NSIs from each context per block were averaged into epochs. Finally, all repeating contexts were averaged together to get the mean repeating context NDI at each epoch.

Although the within-participant and between-participant NSIs cannot be compared against each other, Figure 27 shows that not only are between-participant NSIs from repeating contexts more similar than NSIs from unique contexts, but also that the degree of between-participant similarity is less than within-participant similarity. Because between-participant and within-participant NSIs were not exact, the results indicate that visual scans were not produced solely from exogenous influences, but were produced from a mix of endogenous and exogenous influences as argued by Josephson and Holmes (2002).

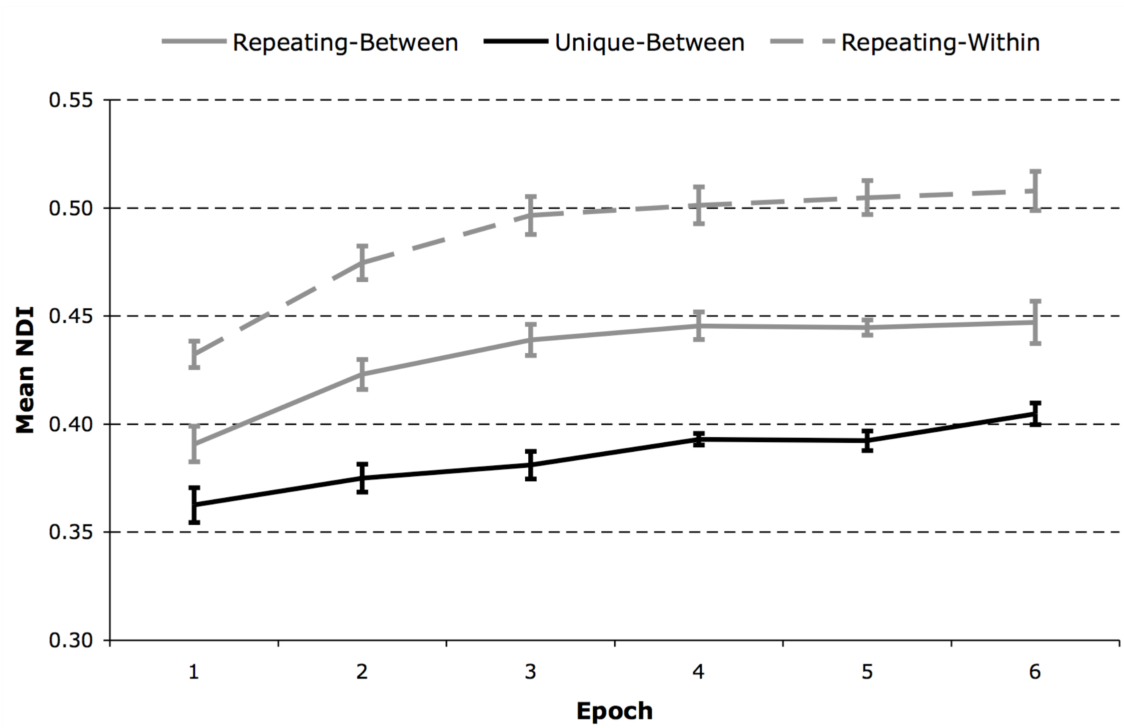

Figure 27. Between-participant and within-participant scan pattern similarities from repeating and unique contexts in experiment 3. Error bars represent standard error.

Experiment 3 was designed to determine if different people scan the same repeating contexts in a similar manner. Furthermore, dual-tasks are argued to provide exogenous processes greater opportunity to influence eye movements, and Figure 22 shows that dual-task scenarios decrease visual scan similarity. This result suggests that repeating scan patterns from repeating contexts are partly the result of endogenous processes that are overridden when scanning in a dual-task scenario.

2.3.3 Experiment 3 Conclusions

There were four goals for experiment 3. The first goal was to increase the likelihood of producing contextual cueing effects (estimated by response time) by reducing the size of the target and distractors. The second goal was to manipulate the cueing effect by adding dual-task conditions. The third goal was to determine the presence/absence of each of the three hallmarks of visual scan refinement, which was facilitated by reducing the size of stimulus items. A corollary goal was to determine if different people scan the same stimulus in a similar manner. Finally, the degree to which dual-task scenarios disrupt scanning was determined.

Like experiment 2, experiment 3 failed to duplicate contextual cueing effects using the traditional dependent variable of mean response time across epochs of trials in any of the transfer conditions (SS, SD, DS, or DD).

The visual scanning refinement analyses corroborate the results from experiments 1 and 2, providing further support for FAST in that all three criteria were met. Experiment 3 shows that repeating scan patterns may come with the cost of increasing dwell durations – repeating contexts had a mean dwell duration that was greater than unique contexts.

First, although contextual cueing, measured by response time, did not occur, all three necessary hallmarks of scanning refinement were present. Second, dual-task scenarios failed to eliminate refinement, demonstrating that refinement can occur during dual-task scenarios, but to a lesser degree relative to single-task scenarios. Third, visual scan refinement as a strictly exogenous strategy can be ruled out because between-participant NSIs for repeating contexts was not identical to within-participant NSIs.

3. Summary and Conclusions

Functionally adaptive scanning theory (FAST) was introduced as a theory of adaptation to repeated visual search. FAST is an incorporation of the phenomena of repeating scan patterns with behavior refinement. FAST is different from existing theories of repeating scan patterns, such as scanpath theory. Where scanpath theory posits repeating scan patterns are the sole result of endogenous influences, FAST maintains that repeating scan patterns are the result of statistical regularities in task environments that lead to scan pattern refinement. Consequently, FAST has 3 refinement criteria of repeating scan patterns: (1) the number of dwells to find a target will decrease across repeated views of a stimulus; (2) scan patterns increase in similarity across repeated searches through the same stimulus; and (3) scan patterns from repeating stimuli become more similar at a faster rate than scan pattern similarity from unique stimuli. The 3 criteria of FAST also provide a new metric for detecting benefits from repeatedly searching through the same stimulus–the phenomenon known as contextual cueing. Three experiments were conducted to shed light on the accuracy of FAST, uncover its limitations, and direct future research.

There were two goals of the first experiment. First was to provide support for FAST. Second was to counter previously reported data demonstrating that eye movements were unnecessary to elicit contextual cueing benefits (Chun & Jiang, 1998). In support of FAST, the first criterion, the number of dwells to find a target decrease across repeated views of a stimulus, was present in experiment 1. Interestingly, the number of dwells to find the target in repeating contexts was reduced with experience, and was statistically indistinguishable from the number of dwells reduced in unique contexts. This is likely a result of the experimental design. Because there were only 12 possible target locations used in unique contexts across the experiment, it is possible that participants picked up on this regularity and used it to their advantage. Indeed, reducing the number of dwells to find the target in unique contexts could help explain why response times in unique contexts get faster with experience (see Figure 3).

Evidence for FASTs 2nd criterion, scan patterns increase in similarity across repeated searches through the same stimulus, was also found in experiment 1. Interestingly, scan pattern similarities from unique contexts also increased with experience at a similar rate when compared to scan patterns from repeating contexts. Consequently, FAST's 3rd criterion, scan patterns from repeating contexts increase in similarity at a faster rate than patterns from unique contexts, was not present in experiment 1. Again, the increasing similarity of unique contexts is likely a function of a small number of possible target locations used in unique contexts. Experiment 1 provides evidence for a weak interpretation of FAST, scanning analyses produced evidence for FAST's first two criteria, but failed to produce evidence for the third (see Table 3, below).

What lead to the absence of criterion 3 in experiment 1? Figure 7 shows that differences between scan pattern similarities from repeating and unique contexts had emerged within the first epoch. A step-wise scan pattern analysis was conducted to determine if the 3rd criterion was present within the first 6 views of repeating and unique contexts. Interestingly and surprisingly, the first two visual scans from repeating contexts were found to be more similar than the first two scans from unique contexts, and this is precisely what Stark and colleagues propose in scanpath theory.

There was also evidence that eye movements play a role during contextual cueing. Chun & Jiang's (experiment 5, 1998) testing-phase accuracy result (repeating contexts result in a higher response accuracy than unique contexts) must be interpreted cautiously as eye movement controls were less than adequate. Indeed, all that can be interpreted from their testing-phase accuracy result is that briefly displayed contexts result in a reduction in response accuracy from the training phase, and that repeating contexts result in a smaller reduction than unique contexts. It is beyond the scope of the results to conclude that eye movements did not contribute to the repeating context benefit, and eye movements could still occur during the testing phase. Consequently, eye movement control was increased in the experiment 1 maximum-control group.

Experiment 1 used a paradigm very similar to Chun and Jiang's experiment 5 (1998), and produced a reliable contextual cueing effect during the training phase. However, experiment 1 did not duplicate Chun & Jiang's testing-phase accuracy results (see Table 1). Moreover, response accuracy from repeating contexts was lower than from unique contexts in the maximum-control condition, and response accuracy from repeating contexts was higher than from unique contexts in the minimum-control condition. This result suggests that increases in eye movement controls hinder cueing effects even though the condition (maximum-control, minimum-control) x context-type (repeating, unique) interaction on testing-phase response accuracy was not significant. These response accuracy trends are predicted when eye movements are considered important to contextual cueing, and are opposite of the trends predicted when eye movements are believed to be unimportant to contextual cueing. Experiment 1 provides weak evidence for the importance of eye movements during contextual cueing.

Experiment 2 was conducted to further test FAST and to determine if gaze-contingent crosshairs affected testing-phase accuracy in experiment 1. The paradigm was nearly identical to Chun and Jiang's (experiment 5, 1998), and only differed in a seemingly minor detail–the dwell control was a + rather than a •. Experiment 2 failed to establish a contextual cueing effect in the training phase. Interestingly, testing-phase response accuracy results from gaze-contingent and static crosshairs were approximately equal to, or less than, the testing-phase response accuracy from the minimum-control group of experiment 1 (see Table 2). It is impossible to determine the importance of eye movements in contextual cueing in experiment 2 because cueing was not established by the end of the training phase. However, experiment 2 provided an opportunity to test FAST's criteria when contextual cueing was not established with trial response times.

Scan pattern analyses again produced FAST's first two criteria, but failed to produce the third. Interestingly, these results occurred in the absence of a reliable contextual cueing effect measured with response time (see Table 3, below). Indeed the presence of FAST's first two criteria in experiment 2 duplicated the results from experiment 1, providing more evidence that scan patterns are repeated in goal-oriented tasks (e.g., visual search), that the number of dwells composing scan patterns are reduced with experience, and that scan pattern similarity increases with experience. Unfortunately, the third FAST criterion, scan patterns from repeating stimuli will increase in similarity at a faster rate than scan patterns from unique contexts, was not present in experiment 2.

Another step-wise scan pattern analysis was conducted to determine if the 3rd criterion was present within the first 6 scans of experiment 2. As in experiment 1, the first two visual scans from repeating contexts were found to be more similar than the first two scans from unique contexts in experiment 2.

Finally, experiment 3 was designed to obtain FASTs 3rd criterion and ensure a contextual cueing effect (measured in response times) by extending the number of search trials from 480 (20 blocks; 4 epochs) to 720 (30 blocks; 6 epochs). Experiment 3 also included a 4 transfer-load conditions designed to help determine if scan pattern refinement was the result of implicit processes or explicit strategies–if scan pattern refinement is implicit, it will not be eliminated in a dual-task scenario. As in experiment 2, contextual cueing did not occur in either the single-single or dual-dual transfer-load conditions. Contextual cueing is a regularly reported phenomenon (Chun, 2000; Chun & Jiang, 1998; Jiang & Wagner, 2004; Song & Jiang, 2005); however, only 1 of 3 experiments reported here produced the effect. Indeed, other researchers have reported having difficult with producing the effect (see Lleras & Von Muhlenen, 2004). It is impossible to determine just how difficult it is to establish the contextual cueing effect as research not duplicating the effect may be difficult to publish. The current research indicates that a better measure for detecting contextual cueing is FAST's criteria.

Scanning analyses were performed on experiment 3 data, and produced support for all three criteria (see Table 3). Furthermore, experiment 3 also showed that dual-task scenarios affect the similarity of scan patterns during the early blocks, but does not when the dual-task is introduced after blocks of only the search task.

Table 3. FAST criteria and contextual cueing results present (✓) or absent (✕) from each experiment.

Experiments	FAST Criteria			Contextual Cueing	
	1	2	3	Training	Testing
Exp. 1	✓	✓	✕	✓	✕
Exp. 2	✓	✓	✕	✕	✕
Exp. 3	✓	✓	✓	✕	N/A

The three experiments taken as a whole have implications for four areas of research. First, results from the experiments can be used to help understand endogenous and exogenous influences on visual scans. Second, the results support theories of repeating scan patterns. Third, the experiments argue the need to reevaluate the phenomena of contextual cueing. Finally, the results support the occurrence of behavioral refinement on visual scans. Each of these facets will be elaborated in the following sections. The thesis will be concluded with FAST's validity, limitations, and directions for future research.

3.1 Endogenous and Exogenous Influences on Scan Patterns

Between the extremes of exogenous and endogenous influences are non-deliberate behaviors that serve a goal and appear strategic. The two extremes and the area between them (see Figure 1) are useful for understanding the influences behind repeating scan patterns.

Scans that result from purely endogenous influences are not refined, but are reused repeatedly. Furthermore, scan patterns should repeat at a high degree of similarity within individuals, but have a low degree of similarity across individuals. Although the absence of refinement and highly similar scan pattern repetition within individuals seems like a "straw man," it is precisely what is predicted by scanpath theory (Chernyak & Stark, 2001; Noton & Stark, 1971a, 1971b; Stark & Ellis, 1981; Stark et al., 1980). Repeating scan patterns were not repeated at the same high level of similarity across multiple views of the same stimulus, and instead increased in similarity with experience while the number of dwells composing scan patterns were reduced with experience (see Figures 7, 10, and 21). This trend occurred in all three experiments.

Behavior from purely exogenous influences would not be refined, either. The same stimulus would always influence scan patterns in nearly (on account of noise in the visual system) the same manner, leading to nearly identical repeating scan patterns. Again, repeating scan patterns were not repeated nearly identical across multiple views of the same stimulus, and instead increased in similarity with experience while the number of dwells composing scan patterns were reduced across all three experiments. It is unknown if exogenous influences differ across individuals. If exogenous influences are assumed to be like reflexes (and similar across individuals) then repeating scan patterns on the same stimulus should be similar across individuals. Experiment 3 showed that repeating scan patterns from different individuals on the same set of repeating contexts did not reach the same level of similarity as repeating scan patterns from the same context within participants (see Figure 27).

Interestingly, dwell durations did not differ between repeating and unique contexts in experiments 1 and 2. Eye movements and memory retrievals operating in parallel could explain the absence of this difference in dwell durations. For example, retrieving an ordered set of eye movement commands/locations could be retrieved while executing eye movements and encoding information at visual locations from an earlier retrieval of an ordered set. If contextual information about repeating contexts is stored in memory, adding a secondary task should put strain on retrieving the memory. Furthermore, the strain on memory could increase dwell durations. When transferring from a single-task scenario to a dual-task scenario in experiment 3, repeating configurations resulted in greater dwell durations than unique contexts in the dual-task scenario.

The influences behind scan patterns are clearly difficult to distinguish between with observable behavior. Indeed, experiments 1 and 2 show that neither extreme influence (endogenous or exogenous) is ever the sole influence of scan patterns. Rather, it is more likely that behavior results from influences falling somewhere between these extremes. Learning is assumed to be absent in both extremes. Endogenous influences may occur after learning had ceased such as a settled on and deliberate strategy, while purely exogenous influences are mostly void of learning. Although it would be difficult to differentiate between endogenous and exogenous influences, it is possible determine differences between statistical and endogenous influences, and statistical and exogenous influences. This is because effects of statistical influences are valuable to the process associated to learning and adaptation (Blessing & Anderson, 1996; Gray, Sims, Fu, & Schoelles, 2006; Haider & Frensch, 1999). As experience with a task environment and a paired goal increase, influences may shift from what appear to be exogenous influences to what appear to be to be endogenous influences, though may never become a deliberate or consciously executed strategy.

3.2 Contextual Cueing

The contextual cueing effect was established in only one of the three experiments. Moreover, it has been stated that participants require a specific set of instructions to elicit the effect (Lleras & Von Muhlenen, 2004). Perhaps response time is not sensitive enough to detect the occurrence of contextual cueing, and researchers need to step back and think about what it means to be cued by a search context.

The key claim from the leading proponents of contextual cueing, Chun and Jiang, is that contextual cueing occurs by implicitly learning information associated with a context, and that response times capture the benefit of learning (Chun, 2000; Chun & Jiang, 1998; Chun & Nakayama, 2000; Jiang & Wagner, 2004; Song & Jiang, 2005). In one of three experiments above, contextual cueing was demonstrated using the response time dependent variable.

It can be argued that scan pattern refinement is also implicit. First, theories of behavioral refinement maintain that adaptations to the structure of the task environment are below the threshold of awareness (Ballard, Hayhoe, Pook, & Rao, 1997; Hayhoe, 2000). Second, Siegler and Stern (1998) demonstrate that strategies used by German 4th graders to solve simple math problems (e.g., 8 + 2 – 8 = ??) unconsciously shift from performing all operations to a cancellation strategy (the 8's cancel leaving 2 as the answer). The claim is that scan pattern refinement is synonymous with the unconscious strategy shifts discussed by Siegler and Stern, and that the refinement process is influenced by statistical factors in the environment.

Given that scan pattern refinement is an implicit process, it can be argued that contextual cueing actually occurred in all three of the experiments. In each of the three experiments, the number of dwells was reduced across epochs and the similarity of visual scans on repeating contexts increased with experience. Consequently, it may be appropriate to redefine contextual cueing as scan pattern refinement above and beyond refinement predicted by random visual scanning. Indeed, the newly proposed definition would include experiments that do and do not demonstrate a response-time benefit from repeating contexts.

3.3 Functionally Adaptive Scanning Theory

Repeating scan patterns are scans that are executed in a similar manner across the same stimulus, and occur within and between participants. Indeed, all three experiments show that within-participant scan patterns from repeating contexts are more similar than within-participant scan pattern similarities from unique contexts. Moreover, experiment 3 demonstrated that scan patterns from repeating contexts increase in similarity with experience at a greater rate than scan patterns from unique contexts.

The results from the visual scan refinement analyses of experiments 1 and 2 mostly support FAST – two out of three criteria were supported. Experiment 3 fully supported FAST, as all three criteria were present (see Table 3, above).

Surprisingly, all three experiments also showed the benefits of using a small set of target locations in the unique contexts. First, the number of dwells to find a target in unique contexts was reduced with experience. Second, the similarity of scan patterns from unique contexts increased with experience. In one sense, using a small set of target locations in the unique contexts is a limitation of all three experiments. FAST predicts that if target locations from unique contexts were randomly assigned making the unique contexts truly unique, the number of dwells to find the target would not reduce with experience, and the similarity of scan patterns from truly unique contexts would not increase. In another sense, using a small set of target locations in the unique contexts provided a good demonstration of the sensitivity of visual system to the statistical structure of the task environment. Indeed, repeating contexts had much more reliable information that could be exploited for adaptation (12 locations per repeating context), whereas unique contexts had little reliable information (1 location per unique context). Indeed, further research into FAST must be done to determine when, why and how scan patterns from unique contexts are refined. These are just the first three experiments arguing for a theory of functionally adaptive scanning, and indeed much more work must be done.

In its current form, FAST does not take a strong position on the mechanism behind the refinement of scan patterns; however, there are some possible directions. Much research has addressed how the task environment and human cognitive processes interact (for a summary of the research see Gray, Neth, & Schoelles, in press). Anderson's rational analysis (1990) predicts the tradeoff of costs for benefits during human-environment interactions. Rational analysis is an analytical approach to understanding the mediation between endogenous and exogenous influences, and predicts that humans behave rationally when the statistical structure of the task environment is considered.

Gray's soft constraints theory (Gray, Sims, Fu, & Schoelles, 2006) is the rational analysis framework applied to the 1/3 s level of behavior, or the embodiment level (Ballard, Hayhoe, Pook, & Rao, 1997), and can be interpreted to predict the scheduling of eye movements, manual motor movements, and memory retrievals during interactive behavior. The soft constraints hypothesis provides a direction to understanding how repeating scan patterns change and adapt to the task environment.

It is sometimes important to step back from the study of phenomena to ask about the functional importance the phenomena play in achieving our goals outside the laboratory. Visual scans usually occur to find information, and anything that increases their efficiency has the result of helping us achieve our goals faster. In the non-laboratory world, besides decreasing cost in terms of time (and presumably, resources), efficient scan patterns may be a key factor in finding a target in time to do something about it. Hence, in situations as diverse as piloting a racecar, making a peanut butter and jelly sandwich, and batting a ball, the time required for eye movements may be a cost whereas achieving the goals of the task may be a benefit.

Various low-level tradeoffs in interactive behavior may be mediated by the cost of a process as measured in its execution time and its past probability of success or benefit. This cognitive cost-benefit tradeoff varies with the design of the task environment and may serve as a soft constraint (Gray, Sims, Fu, & Schoelles, 2006; Myers & Gray, submitted) on scan pattern adaptation. The soft constraints hypothesis is a good candidate for understanding scan pattern refinement. It maintains that, from among a set of successful sequences of interactive behaviors (or, *interactive routines*), people tend to select routines that minimize performance costs measured in units of time.

The soft constraints hypothesis is compatible with the views espoused by Ballard and Hayhoe (Ballard, Hayhoe, Pook, & Rao, 1997; Hayhoe, 2000) on the implicit, non-deliberate tradeoffs made between use of memory versus the use of perceptual-motor resources. However, whereas Ballard and associates espouse a minimum-memory hypothesis such that the central controller acts to conserve memory resources by favoring the use of perceptual-motor ones, the soft constraints hypothesis adopts a strict cost-benefit accounting where the cost estimates are made based on time measured in milliseconds.

The soft constraints hypothesis is not a hypothesis of how interactive routines are developed, but is instead a hypothesis for selecting between interactive routines and choosing the one that is takes the shortest amount of time (Gray, Sims, Fu, & Schoelles, 2006). It is unlikely that all possible interactive routines are available to select between when a new goal is encountered. It is more likely that behavior is gradually refined at the 1/3 s to 3 s level of analysis to achieve a goal in a minimum amount of time while maintaining desired task accuracy. Such a behavior-refinement hypothesis is an extension of Haider & Frensch's information-reduction hypothesis (1999).

The information-reduction hypothesis holds that people learn, with practice, to distinguish between task-relevant and task-redundant information and limit processing to task-relevant information. Improvements in task performance reflect an increased knowledge about which information has to be processed and which information has to be avoided. The task-relevant knowledge is hypothesized to be available to consciousness and voluntarily used (Haider & Frensch, 1999). Haider and Frensch show that task-redundant information is actively ignored at a perceptual, rather than conceptual, level of processing.

Like the information-reduction hypothesis, the behavior-refinement hypothesis maintains that repeatedly completing the same goal leads to increased task performance through decreased reaction times. Decreased reaction times result from fewer behaviors (e.g., eye-movements, mouse-movements, mouse-clicks, etc.) necessary to complete the goal. Behaviors that reliably lead to the successful completion of the goal would persist, while irrelevant, unreliable, and unnecessary information acquisition would be removed from the sequence of behaviors. Eventually, the sequence would become routine and executed regularly. Soft constraints hypothesis then predicts that the most efficient interactive routine for completing a goal is selected through cognitive cost-benefit accounting.

The behavior-refinement hypothesis adds to the information-reduction hypothesis by asserting that behavior is gradually refined through the same, or similar, cognitive cost-benefit accounting process suggested by soft constraints hypothesis. Refined and regularly used sequences of behaviors then become Gray et al.'s interactive routines.

An example supporting the behavior-refinement hypothesis is provided by Myers and Gray (submitted). Myers and Gray showed that initial saccades favored salient, attention-capturing areas within a visual search task at levels greater than chance. Participants were predicted to gradually eliminate saccades to salient areas with experience when the target was never located in the salient area. This would effectively eliminate the acquisition of unreliable information, and is predicted by the information-reduction and behavior-refinement hypotheses. Further support for the behavior-refinement hypothesis comes from a simple mathematical model developed by Myers and Gray that accurately predicted the proportion of initial saccades to the salient area as a function of noise in the visual system and the time saved by avoiding the area. Indeed, the cost of a single dwell-saccade pair that never obtained task-relevant information was eliminated from behavior (Myers & Gray, submitted), as predicted by the behavior-refinement hypothesis.

The behavior-refinement hypothesis thus predicts that interactive behaviors (e.g., eye-movements, mouse-movements, mouse-clicks, etc.) are used in a similar sequence, given a specific goal and task environment. Consequently, repeating patterns of interactive behavior will occur across repeatedly completing goals in the same task environment. Over time, behaviors determined to be useless to completing the goal will be removed from the sequence of behaviors, resulting in refined and efficient behavioral sequences that maintain accuracy while effectively reducing the goal completion time.

The behavior-refinement hypothesis asserts that behavior can be refined into interactive routines through a strict cost-benefit accounting, as suggested in the soft constraints hypothesis. This same cognitive accounting hypothesis has been used to predict the selection between interactive routines during interactive behavior (Gray, Sims, Fu, & Schoelles, 2006).

Understanding how FAST, and improved understanding of scan patterns, can be applied to real-world issues helps to provide an example of the usefulness of scan pattern research. An example of applying understanding based on this research can be provided with a training scenario. Imagine training pilots to scan their flight instruments in a particular sequence. Differences between scan patterns can be detected in real-time during the training scenario allowing trainers to easily determine if the flight instruments were scanned in the instructed order, and if differences in scanning strategies lead to different training outcomes, such as missions success and failure.

3.4 Summary

The three experiments provide support for FAST. The number of dwells was reduced as experience increased with the goal of finding a target among distractors. Scan patterns increased in similarity with experience, and scan patterns from repeating contexts increased with experience at a faster rate than scan patterns from unique contexts in experiment 3. Interestingly, increased cognitive load was shown to disrupt scan pattern similarity, and increase dwell durations on items in repeating contexts. These results suggest an endogenous component in scan pattern repetition and refinement. Moreover, scan patterns from repeating contexts viewed between participants were found to be more similar than unique contexts, indicating an exogenous component in scan pattern repetition and refinement. Between the poles of exogenous and endogenous influences lie statistical influences. Statistical influences, such as stimulus reliability over time, were concluded to be the driving forces behind scan pattern refinement and adaptation based on the fact that scan patterns were refined with experience.

The FAST criteria of scan pattern refinement and adaptation can be used as a more sensitive metric than trial response time for contextual cueing. Given refinement is an implicit process, it can be argued that contextual cueing actually occurred in all three of the experiments. Consequently, it may be appropriate to redefine contextual cueing as the scan pattern refinement process that results in scan pattern similarities that are greater than the similarity between random scan patterns.

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5. Appendix A: Experiment 1 ANOVA Tables

Table A1

Mixed Analysis of Variance for Training-phase Gaze Control

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.136	0.715	0.004
Context * Task	1	0.512	0.479	0.015
Error(Context)	34			
Block	**4.683**	**2.75**	**0.023**	**0.075**
Block * Task	4.683	1.764	0.128	0.049
Error(Block)	159.205			
Context * Block	8.201	0.892	0.526	0.026
Context * Block * Task	8.201	1.068	0.386	0.03
Error(Context*Block)	278.82			
	Between subjects			
Task	**1**	**12.913**	**0.001**	**0.275**
Error	34			

Computed using alpha = .05

Table A2

Mixed Analysis of Variance for Training-phase Accuracy

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.388	0.537	0.01
Context * Task	1	0.524	0.473	0.014
Error(Context)	38			
Block	9.591	1.105	0.358	0.028
Block * Task	9.591	1.019	0.425	0.026
Error(Block)	364.442			
Context * Block	11.696	0.671	0.776	0.017
Context * Block * Task	11.696	1.358	0.185	0.035
Error(Context*Block)	444.462			
	Between subjects			
Task	1	2.11	0.155	0.053
Error	38			

Computed using alpha = .05

Table A3

Mixed Analysis of Variance for Training-phase Response Time

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.779	0.383	0.021
Context * Task	1	2.231	0.144	0.057
Error(Context)	37			
Block	**4.512**	**25.923**	**0.000**	**0.412**
Block * Task	4.512	0.674	0.629	0.018
Error(Block)	166.952			
Context * Block	8.549	1.537	0.138	0.040
Context * Block * Task	8.549	1.217	0.286	0.032
Error(Context*Block)	316.301			
	Between subjects			
Task	1	1.756	0.193	0.045
Error	38			

Computed using alpha = .05

Table A4

Mixed Analysis of Variance for Response Times using only Epochs 1 and 4 from the Experiment 1 Training Phaase

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.193	0.663	0.005
Context * Task	1	2.668	0.111	0.066
Error(Context)	38			
Epoch	**1**	**19.015**	**0**	**0.334**
Epoch * Task	1	0.169	0.683	0.004
Error(Epoch)	38			
Context * Epoch	**1**	**4.602**	**0.038**	**0.108**
Context * Epoch * Task	1	0.044	0.836	0.001
Error(Context*Epoch)	38			
	Between subjects			
Task	1	1.003	0.323	0.026
Error	38			

Computed using alpha = .05

Table A5
Mixed Analysis of Variance for Testing-phase Gaze Control

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.083	0.775	0.002
Context * Task	1	0.518	0.476	0.015
Error(Context)	35			
Block	2.882	0.231	0.868	0.007
Block * Task	2.882	0.146	0.926	0.004
Error(Block)	100.887			
Context * Block	5.218	0.518	0.770	0.015
Context * Block * Task	5.218	1.039	0.397	0.029
Error(Context*Block)	182.645			
	Between subjects			
Task	**1**	**7.852**	**0.008**	**0.183**
Error	34			

Computed using alpha = .05

Table A6
Mixed Analysis of Variance for Testing-phase Response Time

Source	df	F	Sig.	η
		Within subjects		
Context	1	1.4073	0.2431	0.0366
Context * Task	1	2.1974	0.1467	0.0561
Error(Context)	37			
Block	**4.316**	**2.5598**	**0.0367**	**0.0647**
Block * Task	4.316	1.0217	0.4010	0.0269
Error(Block)	159.693			
Context * Block	4.897	0.9289	0.4621	0.0245
Context * Block * Task	4.897	0.9621	0.4413	0.0253
Error(Context*Block)	181.185			
		Between subjects		
Task	1	1.113	0.298	0.029
Error	37			

Computed using alpha = .05

Table A7
Mixed Analysis of Variance for Testing-phase Accuracy

Source	df	F	Sig.	η
		Within subjects		
Context	1	0.001	0.976	0.000
Context * Task	1	1.867	0.180	0.048
Error(Context)	37			
Block	9	0.750	0.663	0.020
Block * Task	9	1.353	0.209	0.035
Error(Block)	333			
Context * Block	9	0.710	0.700	0.019
Context * Block * Task	9	1.568	0.123	0.041
Error(Context*Block)	333			
		Between subjects		
Task	1	2.128	0.153	0.054
Error	38			

Computed using alpha = .05

Table A8
Mixed Analysis of Variance for Training-phase Dwell Number

Source	df	F	Sig.	η
		Within subjects		
Context	1	3.1785	0.0838	0.0879
Context * Task	1	0.2439	0.6247	0.0073
Error(Context)	33			
Block	**8.929**	**24.0301**	**0.0000**	**0.4214**
Block * Task	8.929	0.8234	0.5942	0.0243
Error(Block)	294.6678			
Context * Block	10.788	1.3477	0.1978	0.0392
Context * Block * Task	10.788	1.6170	0.0936	0.0467
Error(Context*Block)	355.9896			
		Between subjects		
Task	1	1.392	0.247	0.040
Error	33			

Computed using alpha = .05

Table A9

Mixed Analysis of Variance for Training-phase Re-dwell Number

Source	df	F	Sig.	η
Within subjects				
Context	1	0.3303	0.5694	0.0099
Context * Task	1	0.0694	0.7939	0.0021
Error(Context)	33			
Block	**7.475**	**2.1803**	**0.0330**	**0.0620**
Block * Task	7.475	0.8994	0.5124	0.0265
Error(Block)	246.659			
Context * Block	8.227	1.0491	0.3999	0.0308
Context * Block * Task	8.227	1.0791	0.3780	0.0317
Error(Context*Block)	271.491			
Between subjects				
Task	1	1.392	0.247	0.040
Error	33			

Computed using alpha = .05

Table A10

Mixed Analysis of Variance of Training-phase Scan Patterns Using Normalized Similarity Index

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**111.725**	**0.0000**	**0.7720**
Context * Task	1	0.2814	0.5994	0.0085
Error(Context)	33			
Epoch	**2.083**	**54.7490**	**0.0000**	**0.6239**
Epoch * Task	2.083	0.6803	0.5156	0.0202
Error(Epoch)	68.751			
Context * Epoch	3.000	1.8873	0.1366	0.0541
Context * Epoch * Task	3.000	0.3453	0.7926	0.0104
Error(Context*Epoch)	99.000			
Between subjects				
Task	1	0.346	0.561	0.010
Error	33			

Computed using alpha = .05

Table A11

Mixed Analysis of Variance of Training-phase Step-wise Scan Pattern Comparisons using Normalized Similarity Index

Source	df	F	Sig.	η
	Within subjects			
Context	**1**	**5.2724**	**0.0280**	**0.1343**
Context * Task	1	0.3510	0.5575	0.0102
Error(Context)	34			
Comparison	4	0.1738	0.9515	0.0051
Comparison * Task	4	0.7872	0.5354	0.0226
Error(Comparison)	34			
Context * Comparison	4	0.4173	0.7959	0.0121
Context * Comparison * Task	4	0.1352	0.9691	0.0040
Error(Context*Comparison)	136			
	Between subjects			
Task	1	0.524	0.474	0.015
Error	34			

Computed using alpha = .05

Table A12

Mixed Analysis of Variance for Training-phase Dwell Duration

Source	df	F	Sig.	η
	Within subjects			
Context	1	1.8453	0.1835	0.0530
Context * Task	1	0.0056	0.9407	0.0002
Error(Context)	33			
Block	**6.936**	**4.8880**	**0.0000**	**0.1290**
Block * Task	6.936	1.4722	0.1787	0.0427
Error(Block)	228.9041			
Context * Block	10.772	1.0207	0.4268	0.0300
Context * Block * Task	10.772	0.8066	0.6310	0.0239
Error(Context*Block)	355.4801			
	Between subjects			
Task	1	0.001	0.980	0.000
Error	33			

Computed using alpha = .05

6. Appendix B: Experiment 2 ANOVA Tables

Table B1

Mixed Analysis of Variance for Gaze Control

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.324	0.573	0.009
Context * Task	1	0.000	0.988	0.000
Error(Context)	35			
Block	5.253	0.991	0.427	0.028
Block * Task	5.253	1.184	0.318	0.033
Error(Block)	183.855			
Context * Block	9.045	0.999	0.441	0.028
Context * Block * Task	9.045	1.513	0.142	0.041
Error(Context*Block)	316.577			
	Between subjects			
Task	1	0.041	0.841	0.001
Error	35			

Computed using alpha = .05

Table B2

Mixed Analysis of Variance for Response Accuracy

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.000	0.997	0.000
Context * Task	1	0.018	0.895	0.000
Error(Context)	37			
Block	10.521	1.206	0.283	0.032
Block * Task	10.521	1.435	0.159	0.037
Error(Block)	389.290			
Context * Block	10.897	0.699	0.738	0.019
Context * Block * Task	10.897	1.414	0.164	0.037
Error(Context*Block)	403.191			
	Between subjects			
Task	1	0.501	0.484	0.013
Error	37			

Computed using alpha = .05

Table B3

Analysis of Variance for Response Time

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.115	0.736	0.003
Context * Task	1	1.296	0.263	0.036
Error(Context)	35			
Block	**7.306**	**35.731**	**0.000**	**0.50517**
Block * Task	7.306	0.711	0.669	0.020
Error(Block)	255.698			
Context * Block	9.903	0.567	0.839	0.016
Context * Block * Task	9.903	0.756	0.670	0.021
Error(Context*Block)	346.608			
	Between subjects			
Task	1	2.037	0.162	0.055
Error	35			

Computed using alpha = .05

B4

Mixed Analysis of Variance for Response Times using only Epochs 1 and 4 from the Experiment 2 Training Phaase

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.094	0.761	0.003
Context * Task	1	1.844	0.183	0.05
Error(Context)	35			
Epoch	1	109.584	< 0.001	0.758
Epoch * Task	1	0.973	0.331	0.027
Error(Epoch)	35			
Context * Epoch	1	1.326	0.257	0.036
Context * Epoch * Task	1	2.394	0.131	0.064
Error(Context*Epoch)	35			
	Between subjects			
Task	1	1.79	0.19	0.049
Error	35			

Computed using alpha = .05

Table B5

Analysis of Variance for Gaze Control

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.003	0.959	0.000
Context * Task	1	0.792	0.380	0.024
Error(Context)	32			
Block	**5.958**	**2.241**	**0.041**	**0.065**
Block * Task	5.958	1.013	0.418	0.031
Error(Block)	190.645			
Context * Block	5.570	0.715	0.628	0.022
Context * Block * Task	5.570	1.634	0.146	0.049
Error(Context*Block)	178.255			
	Between subjects			
Task	1	0.003	0.960	0.000
Error	32			

Computed using alpha = .05

Table B6

Mixed Analysis of Variance for Response Time from the testing phase of experiment 2.

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.034	0.854	0.001
Context * Task	1	0.032	0.859	0.001
Error(Context)	36			
Block	**5.328**	**5.868**	**0.000**	**0.140**
Block * Task	5.328	0.428	0.840	0.012
Error(Block)	191.800			
Context * Block	6.185	1.320	0.248	0.035
Context * Block * Task	6.185	0.707	0.649	0.019
Error(Context*Block)	222.655			
	Between subjects			
Task	1	0.021	0.886	0.001
Error	36			

Computed using alpha = .05

Table B7

Mixed Analysis of Variance for Accuracy in testing phase of experiment 2

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.065	0.801	0.002
Context * Task	1	0.031	0.862	0.001
Error(Context)	36			
Block	**9**	**2.237**	**0.020**	**0.059**
Block * Task	9	0.936	0.494	0.025
Error(Block)	324			
Context * Block	**9**	**2.259**	**0.018**	**0.059**
Context * Block * Task	9	0.891	0.534	0.024
Error(Context*Block)	324			
	Between subjects			
Task	1	3.480	0.070	0.088
Error	36			

Computed using alpha = .05

Table B8

Mixed Analysis of Variance for Number of Dwells in training phase of experiment 2

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.4850	0.4908	0.0137
Context * Task	1	0.6095	0.4402	0.0171
Error(Context)	35			
Block	**4.393**	**12.0031**	**0.0000**	**0.2554**
Block * Task	4.393	0.9667	0.4329	0.0269
Error(Block)	153.7621			
Context * Block	9.969	0.9856	0.4554	0.0274
Context * Block * Task	9.969	0.9564	0.4813	0.0266
Error(Context*Block)	348.9042			
	Between subjects			
Task	1	0.137	0.714	0.004
Error	35			

Computed using alpha = .05

Table B9

Mixed Analysis of Variance for Re-dwells from the training phase of experiment 2

Source	df	F	Sig.	η
	Within subjects			
Context	1	0.1384	0.7121	0.0039
Context * Task	1	0.5914	0.4470	0.0166
Error(Context)	35			
Block	**7.370**	**3.0586**	**0.0035**	**0.0804**
Block * Task	7.370	1.5862	0.1356	0.0434
Error(Block)	257.954			
Context * Block	19.000	0.6336	0.8821	0.0178
Context * Block * Task	19.000	0.6874	0.8335	0.0193
Error(Context*Block)	665			
	Between subjects			
Task	1	0.000	0.987	0.000
Error	35			

Computed using alpha = .05

Table B10

Mixed Analysis of Variance for Normalized Similarity Index from training phase of experiment 2

Source	df	F	Sig.	η
	Within subjects			
Context	**1**	**106.0805**	**0.0000**	**0.7683**
Context * Task	1	0.2817	0.5992	0.0087
Error(Context)	35			
Epoch	**2.181**	**36.1317**	**0.0000**	**0.5303**
Epoch * Task	2.181	0.3203	0.7455	0.0099
Error(Epoch)	69.788			
Context * Epoch	3.000	0.7955	0.4993	0.0243
Context * Epoch * Task	3.000	1.0998	0.3531	0.0332
Error(Context*Epoch)	99.000			
	Between subjects			
Task	1	1.616	0.213	0.048
Error	35			

Computed using alpha = .05

Table B11

Mixed Analysis of Variance for Step-wise Comparisons of Scan Patterns

Source	df	F	Sig.	η
	Within subjects			
Context	**1**	**4.6940**	**0.0372**	**0.1183**
Context * Task	1	0.4313	0.5156	0.0122
Error(Context)	35			
Comparison	3	0.2185	0.8836	0.0062
Comparison * Task	3	1.1685	0.3254	0.0323
Error(Comparison)	105.138			
Context * Comparison	4	0.2019	0.9370	0.0057
Context * Comparison * Task	4	1.2243	0.3033	0.0338
Error(Context*Comparison)	140			
	Between subjects			
Task	1	0.638	0.430	0.018
Error	35			

Computed using alpha = .05

Table B12

Analysis of Variance for Dwell Durations from experiment 2 training phase.

Source	df	F	Sig.	η
	Within subjects			
Context	1	1.0573	0.3109	0.0293
Context * Task	1	0.0000	0.9960	0.0000
Error(Context)	35			
Block	**6.925**	**4.5221**	**0.0001**	**0.1144**
Block * Task	6.925	0.7023	0.6685	0.0197
Error(Block)	242.379			
Context * Block	8.814	0.5472	0.8361	0.0154
Context * Block * Task	8.814	0.7218	0.6859	0.0202
Error(Context*Block)	308.498			
	Between subjects			
Task	1	0.274	0.604	0.008
Error	35			

Computed using alpha = .05

7. Appendix C: Experiment 3 ANOVA Tables

Table C1

Mixed Analysis of Variance on letter classification task accuracy in experiment 3 between dual-dual and dual-single phase-1.

Source	df	F	Sig.	η
Within subjects				
Block	**7.916**	**1.974**	**0.052**	**0.076**
Block * Transfer Condition	7.916	0.341	0.948	0.014
Block * Configuration group	15.833	0.689	0.802	0.054
Block * Transfer Condition * Configuration group	15.833	1.356	0.169	0.101
Error (Block)	189.994			
Between subjects				
Transfer Condition	1	1.045	0.317	0.042
Configuration-group	2	0.352	0.707	0.028
Transfer Condition * Configuration-group	2	1.397	0.267	0.104
Error	24			

Table C2

Mixed Analysis of Variance on letter classification task accuracy in epxeriment 3 between dual-dual and single-dual phase-1.

Source	df	F	Sig.	η
Within subjects				
Block	14	1.032	0.421	0.045
Block * Transfer Condition	14	1.357	0.173	0.058
Block * Configruation group	28	1.242	0.19	0.101
Block * Transfer Condition * Configruation group	28	1.188	0.239	0.097
Error (Block)	308			
Between subjects				
Transfer Condition	1	0.532	0.474	0.024
Configuration-group	2	0.346	0.711	0.030
Transfer Condition * Configuration-group	2	0.340	0.715	0.030
Error	22			

Table C3

Mixed Analysis of Variance on letter classification task accuracy in epxeriment 3 between dual-single and single-dual phase-1 and 2.

Source	df	F	Sig.	η
Within subjects				
Block	**14**	**2.119**	**0.011**	**0.081**
Block * Transfer Condition	14	0.77	0.702	0.031
Block * Configruation group	28	1.015	0.447	0.078
Block * Transfer Condition * Configruation group	28	1.277	0.162	0.096
Error (Block)	336			
Between subjects				
Transfer Condition	1	0.001	0.974	0.000
Configuration-group	2	0.102	0.903	0.008
Transfer Condition * Configuration-group	2	0.099	0.906	0.008
Error	24			

Table C4
Mixed Analysis of Variance on Trial Accuracy

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**11.142**	**0.002**	**0.210**
Context * Transfer Condition	3	1.575	0.210	0.101
Context * Configuration-group	2	1.683	0.198	0.074
Context * Transfer Condition * Configuration-group	6	1.166	0.343	0.143
Error(Context)	42			
Block	**10.373**	**3.150**	**0.001**	**0.070**
Block * Transfer Condition	**87.000**	**2.185**	**0.000**	**0.135**
Block * Configuration-group	20.747	1.217	0.232	0.055
Block * Transfer Condition * Configuration-group	62.240	1.160	0.202	0.142
Error(Block)	435.682			
Context * Block	14.741	0.636	0.843	0.015
Context * Block * Transfer Condition	44.222	1.065	0.362	0.071
Context * Block * Configuration-group	29.482	1.215	0.203	0.055
Context * Block * Transfer Condition * Configuration-group	88.445	0.977	0.542	0.122
Error(Context * Block)	619.115			
Between subjects				
Transfer Condition	3	2.530	0.070	0.153
Configuration-group	2	1.792	0.179	0.079
Transfer Condition * Configuration-group	6	0.635	0.701	0.083
Error	42			

Computed using alpha = .05

Table C5

Mixed Analysis of Variance for Workload Effects on Trial Accuracy

Source	df	F	Sig.	*η*
	Within subjects			
Context	**1**	**4.261**	**0.044**	**0.080**
*Context * Load*	*1*	*3.282*	*0.076*	*0.063*
Context * Configuration-group	2	0.801	0.455	0.032
Context * Load * Configuration-group	2	2.448	0.097	0.091
Error(Context)	49			
Block	**5.944**	**4.249**	**0.000**	**0.080**
*Block * Load*	*5.944*	*1.967*	*0.071*	*0.039*
Block * Configuration-group	11.889	1.219	0.270	0.047
Block * Load * Configuration-group	11.889	1.570	0.100	0.060
Error(Block)	291.269			
Context * Block	9.570	0.449	0.916	0.009
Context * Block * Load	9.570	1.014	0.429	0.020
Context * Block * Configuration-group	19.141	1.181	0.268	0.046
Context * Block * Load * Configuration-group	19.141	0.713	0.807	0.028
Error(Context * Block)	468.949			
	Between subjects			
Load	**1**	**15.031**	**0.000**	**0.235**
Configuration-group	2	1.663	0.200	0.064
Load * Configuration-group	2	0.403	0.670	0.016
Error	49			

Computed using alpha = .05

Table C6

Mixed Analysis of Variance for Workload Effects on Trial Accuracy between Single-Single and Single-Dual Transfer Conditions in Phase 1

Source	df	F	Sig.	*η*
Within subjects				
Context	1	1.332	0.261	0.060
Context * Transfer Condition	1	0.243	0.627	0.011
Context * Configuration-group	2	0.371	0.695	0.034
Context * Transfer Condition * Configuration-group	2	0.882	0.429	0.077
Error(Context)	21			
Block	3.064	0.778	0.513	0.036
Block * Transfer Condition	3.064	0.794	0.504	0.036
Block * Configuration-group	6.128	1.441	0.212	0.121
Block * Transfer Condition * Configuration-group	6.128	1.239	0.298	0.106
Error(Block)	64.343			
Context * Block	5.266	1.477	0.200	0.066
Context * Block * Transfer Condition	5.266	0.362	0.882	0.017
Context * Block * Configuration-group	10.532	0.817	0.618	0.072
Context * Block * Transfer Condition * Configuration-group	10.532	1.606	0.110	0.133
Error(Context * Block)	110.584			
Between subjects				
Transfer Condition	1	0.269916239	0.609	0.013
Configuration-group	2	1.390792647	0.271	0.117
*Transfer Condition * Configuration-group*	*2*	*3.026371968*	*0.070*	*0.224*
Error	21			

Computed using alpha = .05

Table C7

Mixed Analysis of Variance for WorkTransfer Condition Effects on Trial Accuracy between Dual-Single and Dual-Dual Transfer Conditions in Phase 1

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**7.198**	**0.013**	**0.238**
Context * Transfer Condition	1	0.800	0.380	0.034
Context * Configuration-group	2	0.544	0.588	0.045
Context * Transfer Condition * Configuration-group	2	0.560	0.579	0.046
Error(Context)	23			
Block	**5.322**	**4.721**	**0.000**	**0.170**
*Block * Transfer Condition*	*5.322*	*2.131*	*0.062*	*0.085*
Block * Configuration-group	**10.645**	**1.950**	**0.041**	**0.145**
Block * Transfer Condition * Configuration-group	10.645	1.154	0.327	0.091
Error(Block)	122.417			
Context * Block	14	0.742	0.732	0.031
Context * Block * Transfer Condition	14	1.550	0.092	0.063
Context * Block * Configuration-group	28	0.946	0.547	0.076
Context * Block * Transfer Condition * Configuration-group	28	0.871	0.658	0.070
Error(Context * Block)	322			
Between subjects				
Transfer Condition	1	1.635847324	0.214	0.066
Configuration-group	2	1.165550659	0.329	0.092
Transfer Condition * Configuration-group	2	0.405297072	0.671	0.034
Error	23			

Computed using alpha = .05

Table C8

Mixed Analysis of Variance for Transfer Effects on Trial Accuracy between Single-Single and Single-Dual Transfer Conditions in Phase 2

Source	df	F	Sig.	*η*
Within subjects				
Context	*1*	*3.717*	*0.068*	*0.157*
Context * Transfer Condition	1	0.003	0.959	0.000
Context * Configuration-group	**2**	**5.529**	**0.012**	**0.356**
*Context * Transfer Condition * Configuration-group*	*2*	*3.246*	*0.060*	*0.245*
Error(Context)	20			
Block	4.780	0.770	0.569	0.037
Block * Transfer Condition	4.780	1.123	0.353	0.053
Block * Configuration-group	9.559	1.731	0.088	0.148
Block * Transfer Condition * Configuration-group	9.559	1.449	0.174	0.127
Error(Block)	95.593			
Context * Block	6.035	1.158	0.333	0.055
Context * Block * Transfer Condition	6.035	1.127	0.351	0.053
Context * Block * Configuration-group	12.071	1.212	0.282	0.108
Context * Block * Transfer Condition * Configuration-group	12.071	1.116	0.354	0.100
Error(Context * Block)	120.710			
Between subjects				
Transfer Condition	1	2.78882824	0.111	0.122
Configuration-group	2	1.531968445	0.240	0.133
Transfer Condition * Configuration-group	2	0.767866244	0.477	0.071
Error	20			

Computed using alpha = .05

Table C9

Mixed Analysis of Variance for Transfer Effects on Trial Accuracy between Dual-Single and Single-Single Transfer Conditions Phase 2

Source	df	F	Sig.	η
Within subjects				
Context	1	3.090	0.093	0.123
Context * Transfer Condition	1	0.006	0.940	0.000
Context * Configuration-group	2	0.379	0.689	0.033
Context * Transfer Condition * Configuration-group	2	2.514	0.104	0.186
Error(Context)	22			
Block	5.971	1.103	0.364	0.048
Block * Transfer Condition	5.971	1.036	0.405	0.045
Block * Configuration-group	11.942	0.705	0.744	0.060
Block * Transfer Condition * Configuration-group	11.942	0.722	0.727	0.062
Error(Block)	131.367			
Context * Block	14	0.841	0.624	0.037
Context * Block * Transfer Condition	14	0.605	0.861	0.027
Context * Block * Configuration-group	28	1.021	0.440	0.085
Context * Block * Transfer Condition * Configuration-group	28	0.753	0.815	0.064
Error(Context * Block)	308			
Between subjects				
Transfer Condition	1	1.751934608	0.199	0.074
Configuration-group	2	0.774261174	0.473	0.066
Transfer Condition * Configuration-group	2	1.020419243	0.377	0.085
Error	22			

Computed using alpha = .05

Table C10

Mixed Analysis of Variance on Trial Response Time

Source	df	F	Sig.	η
Within subjects				
Context	1	0.563	0.457	0.013
Context * Transfer Condition	3	1.030	0.389	0.066
Context * Configuration-group	2	1.268	0.291	0.054
Context * Transfer Condition * Configuration-group	6	0.785	0.586	0.097
Error(Context)	44			
Block	**3.783**	**14.119**	**0.000**	**0.243**
Block * Transfer Condition	**11.349**	**5.498**	**0.000**	**0.273**
Block * Configuration-group	7.566	0.888	0.524	0.039
Block * Transfer Condition * Configuration-group	22.698	0.979	0.494	0.118
Error(Block)	166.451			
*Context * Block*	*2.475*	*2.346*	*0.089*	*0.051*
Context * Block * Transfer Condition	7.425	1.162	0.330	0.073
Context * Block * Configuration-group	4.950	1.636	0.157	0.069
Context * Block * Transfer Condition * Configuration-group	14.849	1.358	0.182	0.156
Error(Context * Block)	108.894			
Between subjects				
Transfer Condition	**3**	**5.598**	**0.002**	**0.276**
Configuration-group	2	0.911	0.410	0.040
Transfer Condition * Configuration-group	6	0.543	0.773	0.069
Error	44			

Computed using alpha = .05

Table C11
Mixed Analysis of Variance on Trial Response Time for Single-single Epochs 1 and 4

Source	df	F	Sig.	η
Within subjects				
Context	1	0.495	0.496	0.043
Context * Configuration-group	2	1.457	0.275	0.209
Error(Context)	11			
Epoch	**1**	**83.913**	**< 0.001**	**0.884**
Epoch * Configuration-group	2	1.602	0.245	0.226
Error(Epoch)	11			
Context * Epoch	1	0.307	0.591	0.027
Context * Epoch * Configuration-group	2	0.087	0.917	0.016
Error(Context * Epoch)	11			
Between subjects				
Configuration-group	2	0.61	0.561	0.1
Error	11			

Computed using alpha = .05

Table C12
Mixed Analysis of Variance on Trial Response Time for Dual-dual Epochs 1 and 4

Source	df	F	Sig.	η
Within subjects				
Context	1	0.392	0.544	0.034
Context * Configuration-group	2	0.394	0.684	0.067
Error(Context)	11			
Epoch	1	37.554	< 0.001	0.773
Epoch * Configuration-group	2	1.432	0.28	0.207
Error(Epoch)	11			
Context * Epoch	1	0.353	0.565	0.031
Context * Epoch * Configuration-group	2	0.615	0.558	0.101
Error(Context * Epoch)	11			
Between subjects				
Configuration-group	2	2.772	0.106	0.335
Error	11			

Computed using alpha = .05

Table C13

Mixed Analysis of Variance for Workload Effects on Trial Response Time from experiment 3

Source	df	F	Sig.	η
Within subjects				
Context	1	0.003	0.960	0.000
Context * Load	1	1.035	0.314	0.020
Context * Configuration-group	2	0.567	0.571	0.022
Context * Load * Configuration-group	2	0.109	0.897	0.004
Error(Context)	50			
Block	**1.696**	**14.994**	**0.000**	**0.231**
Block * Load	**1.696**	**4.649**	**0.016**	**0.085**
Block * Configuration-group	3.392	1.098	0.359	0.042
Block * Load * Configuration-group	3.392	1.050	0.380	0.040
Error(Block)	84.804			
Context * Block	1.584	2.343	0.114	0.045
Context * Block * Load	1.584	1.333	0.266	0.026
Context * Block * Configuration-group	3.167	1.546	0.207	0.058
Context * Block * Load * Configuration-group	3.167	1.411	0.245	0.053
Error(Context * Block)	79.180			
Between subjects				
Load	**1**	**46.790**	**0.000**	**0.483**
Configuration-group	2	2.645	0.081	0.096
Load * Configuration-group	2	0.148	0.863	0.006
Error	50			

Computed using alpha = .05

Table C14

Mixed Analysis of Variance for Workload Effects on Trial Response Time between Single-Single and Single-Dual Transfer Conditions in Phase 1

Source	df	F	Sig.	η
Within subjects				
Context	1	1.963	0.176	0.085
Context * Transfer Condition	1	0.060	0.809	0.003
Context * Configuration-group	2	0.951	0.402	0.083
Context * Transfer Condition * Configuration-group	2	1.646	0.217	0.135
Error(Context)	21			
Block	**7.569**	**12.351**	**0.000**	**0.370**
Block * Transfer Condition	7.569	0.725	0.662	0.033
Block * Configuration-group	15.137	0.877	0.592	0.077
Block * Transfer Condition * Configuration-group	15.137	0.542	0.915	0.049
Error(Block)	158.939			
Context * Block	6.507	1.821	0.093	0.080
Context * Block * Transfer Condition	6.507	1.484	0.183	0.066
Context * Block * Configuration-group	13.014	0.773	0.688	0.069
Context * Block * Transfer Condition * Configuration-group	13.014	0.783	0.677	0.069
Error(Context * Block)	136.652			
Between subjects				
Transfer Condition	1	0.019	0.891	0.001
Configuration-group	2	1.740	0.200	0.142
Transfer Condition * Configuration-group	2	0.041	0.960	0.004
Error	21			

Computed using alpha = .05

Table C15

Mixed Analysis of Variance for WorkTransfer Condition Effects on Trial Response Time between Dual-Single and Dual-Dual Transfer Conditions in Phase 1

Source	df	F	Sig.	*η*
Within subjects				
Context	1	0.020	0.889	0.001
Context * Transfer Condition	1	0.840	0.369	0.037
Context * Configuration-group	2	0.624	0.545	0.054
Context * Transfer Condition * Configuration-group	2	1.417	0.264	0.114
Error(Context)	22			
Block	**1.730**	**9.147**	**0.001**	**0.294**
Block * Transfer Condition	1.730	2.613	0.093	0.106
Block * Configuration-group	3.461	1.637	0.191	0.130
Block * Transfer Condition * Configuration-group	3.461	1.106	0.364	0.091
Error(Block)	38.069			
Context * Block	1.674	2.112	0.142	0.088
Context * Block * Transfer Condition	1.674	1.142	0.322	0.049
Context * Block * Configuration-group	3.349	1.718	0.175	0.135
Context * Block * Transfer Condition * Configuration-group	3.349	1.461	0.239	0.117
Error(Context * Block)	36.837			
Between subjects				
Transfer Condition	1	1.594413799	0.220	0.068
Configuration-group	2	0.315929446	0.732	0.028
Transfer Condition * Configuration-group	2	0.254437043	0.778	0.023
Error	22			

Computed using alpha = .05

Table C16

Mixed Analysis of Variance for Transfer Effects on Response Time between Single-Single and Single-Dual Transfer Conditions in Phase 2

Source	df	F	Sig.	η
Within subjects				
Context	1	1.374	0.255	0.064
Context * Transfer Condition	1	0.336	0.569	0.016
Context * Configuration-group	2	0.418	0.664	0.040
Context * Transfer Condition * Configuration-group	2	2.121	0.146	0.175
Error(Context)	20			
Block	7.280	1.764	0.096	0.081
Block * Transfer Condition	7.280	1.337	0.235	0.063
Block * Configuration-group	14.561	0.795	0.678	0.074
Block * Transfer Condition * Configuration-group	14.561	0.797	0.676	0.074
Error(Block)	145.610			
Context * Block	14	0.745	0.728	0.036
Context * Block * Transfer Condition	14	1.372	0.166	0.064
Context * Block * Configuration-group	28	1.126	0.307	0.101
Context * Block * Transfer Condition * Configuration-group	28	1.012	0.453	0.092
Error(Context * Block)	280			
Between subjects				
Transfer Condition	**1**	**15.303**	**0.001**	**0.433**
Configuration-group	2	0.284	0.755	0.028
Transfer Condition * Configuration-group	2	0.171	0.844	0.017
Error	20			

Computed using alpha = .05

Table C17

Mixed Analysis of Variance for Transfer Effects on Trial Accuracy between Dual-Single and Single-Single Transfer Conditions in Phase 2

Source	df	F	Sig.	*η*
Within subjects				
Context	1	0.270	0.609	0.012
Context * Transfer Condition	1	0.029	0.867	0.001
Context * Configuration-group	2	0.460	0.637	0.040
Context * Transfer Condition * Configuration-group	2	1.920	0.170	0.149
Error(Context)	22			
Block	7.541	1.656	0.117	0.070
Block * Transfer Condition	7.541	0.972	0.457	0.042
Block * Configuration-group	15.081	0.932	0.531	0.078
Block * Transfer Condition * Configuration-group	15.081	0.519	0.928	0.045
Error(Block)	165.894			
Context * Block	14	0.972	0.482	0.042
Context * Block * Transfer Condition	14	0.367	0.983	0.016
Context * Block * Configuration-group	28	0.820	0.730	0.069
Context * Block * Transfer Condition * Configuration-group	28	0.843	0.698	0.071
Error(Context * Block)	308			
Between subjects				
Transfer Condition	1	1.203	0.285	0.052
Configuration-group	2	0.493	0.617	0.043
Transfer Condition * Configuration-group	2	0.053	0.948	0.005
Error	22			

Computed using alpha = .05

Table C18

Mixed Analysis of Variance on the number of dwells from experiment 3

Source	df	F	Sig.	η
Within subjects				
Context	1	3.266	0.078	0.075
Context * Transfer Condition	3	0.216	0.885	0.016
Context * Configuration-group	2	1.856	0.169	0.085
Context * Transfer Condition * Configuration-group	6	1.860	0.112	0.218
Error(Context)	40			
Block	**7.861**	**28.660**	**0.000**	**0.417**
Block * Transfer Condition	**23.584**	**3.058**	**0.000**	**0.187**
Block * Configuration-group	15.722	0.654	0.836	0.032
Block * Transfer Condition * Configuration-group	47.167	0.745	0.890	0.101
Error(Block)	314.448			
Context * Block	14.309	1.647	0.061	0.040
Context * Block * Transfer Condition	42.926	1.118	0.284	0.077
Context * Block * Configuration-group	28.617	1.143	0.280	0.054
Context * Block * Transfer Condition * Configuration-group	85.852	0.835	0.850	0.111
Error(Context * Block)	572.349			
Between subjects				
Transfer Condition	**3**	**3.383**	**0.027**	**0.202**
Configuration-group	2	1.125	0.335	0.053
Transfer Condition * Configuration-group	6	0.841	0.546	0.112
Error	40			

Computed using alpha = .05

Table C19

Mixed Analysis of Variance for Workload Effects on the number of dwells from experiment 3

Source	df	F	Sig.	η
Within subjects				
Context	1	1.506	0.226	0.032
Context * Load	1	0.018	0.893	0.000
*Context * Configuration-group*	*2*	*3.074*	*0.056*	*0.118*
Context * Load * Configuration-group	**2**	**4.335**	**0.019**	**0.159**
Error(Context)	46			
Block	**6.590**	**21.589**	**< 0.001**	**0.319**
Block * Load	**6.590**	**3.608**	**0.001**	**0.073**
Block * Configuration-group	13.180	0.787	0.675	0.033
Block * Load * Configuration-group	13.180	0.572	0.878	0.024
Error(Block)	6.590			
Context * Block	**8.981**	**2.520**	**0.008**	**0.052**
Context * Block * Load	8.981	1.188	0.301	0.025
Context * Block * Configuration-group	17.962	1.197	0.260	0.049
Context * Block * Load * Configuration-group	17.962	0.814	0.684	0.034
Error(Context * Block)	413.125			
Between subjects				
Load	**1**	**21.781**	**0.000**	**0.321**
Configuration-group	2	0.949	0.394	0.040
Load * Configuration-group	2	1.557	0.222	0.063
Error	46			

Computed using alpha = .05

Table C20

Mixed Analysis of Variance for Workload Effects on Number of Dwells between Single-Single and Single-Dual Transfer Conditions from Phase 1

Source	df	F	Sig.	*η*
Within subjects				
Context	1	0.507	0.486	0.027
Context * Transfer Condition	1	0.011	0.919	0.001
Context * Configuration-group	2	1.644	0.221	0.154
Context * Transfer Condition * Configuration-group	2	2.355	0.123	0.207
Error(Context)	18			
Block	**5.395**	**6.785**	**0.000**	**0.274**
Block * Transfer Condition	5.395	0.441	0.832	0.024
Block * Configuration-group	10.791	0.449	0.927	0.048
Block * Transfer Condition * Configuration-group	10.791	0.799	0.639	0.082
Error(Block)	97.117			
Context * Block	14	1.141	0.323	0.060
Context * Block * Transfer Condition	14	0.939	0.517	0.050
Context * Block * Configuration-group	28	0.621	0.934	0.065
Context * Block * Transfer Condition * Configuration-group	28	0.572	0.961	0.060
Error(Context * Block)	252			
Between subjects				
Transfer Condition	1	0.296	0.593	0.016
Configuration-group	2	0.188	0.830	0.020
Transfer Condition * Configuration-group	2	0.262	0.773	0.028
Error	18			

Computed using alpha = .05

Table C21
Mixed Analysis of Variance for Transfer Condition Effects on Number of Dwells between Dual-Single and Dual-Dual Transfer Conditions from Phase 1

Source	df	F	Sig.	η
Within subjects				
Context	1	0.705	0.410	0.031
Context * Transfer Condition	1	1.246	0.276	0.054
Context * Configuration-group	**2**	**5.291**	**0.013**	**0.325**
Context * Transfer Condition * Configuration-group	2	0.481	0.625	0.042
Error(Context)	22			
Block	**5.230**	**16.539**	**0.000**	**0.429**
Block * Transfer Condition	5.230	1.193	0.317	0.051
Block * Configuration-group	10.461	0.756	0.676	0.064
Block * Transfer Condition * Configuration-group	10.461	0.624	0.798	0.054
Error(Block)	115.067			
Context * Block	**6.873**	**2.302**	**0.030**	**0.095**
Context * Block * Transfer Condition	6.873	1.619	0.135	0.069
Context * Block * Configuration-group	13.746	1.270	0.233	0.104
Context * Block * Transfer Condition * Configuration-group	13.746	1.024	0.432	0.085
Error(Context * Block)	151.203			
Between subjects				
Transfer Condition	1	0.001	0.975	0.000
Configuration-group	2	1.592	0.226	0.126
Transfer Condition * Configuration-group	2	0.319	0.730	0.028
Error	22			

Computed using alpha = .05

Table C22

Mixed Analysis of Variance for Transfer Effects on Number of Dwells between Phase 2 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	*η*
Within subjects				
Context	1	3.436	0.080	0.160
Context * Transfer Condition	1	0.032	0.860	0.002
Context * Configuration-group	2	0.516	0.605	0.054
Context * Transfer Condition * Configuration-group	2	0.443	0.649	0.047
Error(Context)	18			
Block	**14**	**1.799**	**0.039**	**0.091**
Block * Transfer Condition	14	0.366	0.983	0.020
Block * Configuration-group	28	0.412	0.997	0.044
Block * Transfer Condition * Configuration-group	28	0.828	0.717	0.084
Error(Block)	252			
Context * Block	7.810	0.480	0.865	0.026
Context * Block * Transfer Condition	7.810	1.317	0.241	0.068
Context * Block * Configuration-group	15.620	1.466	0.122	0.140
Context * Block * Transfer Condition * Configuration-group	15.620	0.776	0.707	0.079
Error(Context * Block)	140.577			
Between subjects				
Transfer Condition	1	3.575	0.075	0.166
Configuration-group	2	0.098	0.907	0.011
Transfer Condition * Configuration-group	2	2.576	0.104	0.223
Error	18			

Computed using alpha = .05

Table C23

Mixed Analysis of Variance for Transfer Effects on Number of Dwells between Phase 2 Dual-Single and Single-Single Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	1	1.508	0.234	0.070
Context * Transfer Condition	1	0.663	0.425	0.032
Context * Configuration-group	2	0.366	0.698	0.035
Context * Transfer Condition * Configuration-group	2	2.032	0.157	0.169
Error(Context)	20			
Block	**14**	**2.369**	**0.004**	**0.106**
Block * Transfer Condition	14	1.378	0.163	0.064
Block * Configuration-group	28	0.817	0.734	0.075
Block * Transfer Condition * Configuration-group	28	1.168	0.261	0.105
Error(Block)	280			
Context * Block	14	0.669	0.804	0.032
Context * Block * Transfer Condition	14	1.120	0.340	0.053
Context * Block * Configuration-group	28	0.797	0.761	0.074
Context * Block * Transfer Condition * Configuration-group	28	1.212	0.218	0.108
Error(Context * Block)	280			
Between subjects				
Transfer Condition	1	0.641356559	0.433	0.031
Configuration-group	2	0.6235101	0.546	0.059
Transfer Condition * Configuration-group	2	1.230256618	0.313	0.110
Error	20			

Computed using alpha = .05

Table C24

Mixed Analysis of Variance on Number of Re-dwells

Source	df	F	Sig.	η
Within subjects				
Context	1	0.665	0.420	0.016
Context * Transfer Condition	3	1.300	0.288	0.089
Context * Configuration-group	2	0.255	0.776	0.013
Context * Transfer Condition * Configuration-group	6	1.479	0.210	0.182
Error(Context)	40			
Block	**7.027**	**19.733**	**0.000**	**0.330**
Block * Transfer Condition	**21.081**	**3.931**	**0.000**	**0.228**
Block * Configuration-group	14.054	0.543	0.906	0.026
Block * Transfer Condition * Configuration-group	42.163	0.718	0.903	0.097
Error(Block)	281.085			
Context * Block	10.131	1.309	0.222	0.032
Context * Block * Transfer Condition	30.394	1.078	0.359	0.075
Context * Block * Configuration-group	20.262	1.372	0.130	0.064
Context * Block * Transfer Condition * Configuration-group	60.787	1.062	0.359	0.137
Error(Context * Block)	405.247			
Between subjects				
Transfer Condition	**3**	**5.029**	**0.005**	**0.274**
Configuration-group	2	1.438	0.249	0.067
Transfer Condition * Configuration-group	6	0.705	0.647	0.096
Error	40			

Computed using alpha = .05

Table C25
Mixed Analysis of Variance for Workload Effects on Re-dwells

Source	df	F	Sig.	η
Within subjects				
Context	1	0.037	0.848	0.001
Context * Load	1	0.333	0.567	0.007
Context * Configuration-group	2	0.700	0.502	0.030
Context * Load * Configuration-group	2	2.133	0.130	0.085
Error(Context)	46			
Block	**4.793**	**14.837**	**0.000**	**0.244**
Block * Load	**4.793**	**4.713**	**0.001**	**0.093**
Block * Configuration-group	9.587	0.573	0.829	0.024
Block * Load * Configuration-group	9.587	0.632	0.779	0.027
Error(Block)	220.494			
Context * Block	6.709	1.602	0.138	0.034
Context * Block * Load	6.709	1.109	0.357	0.024
Context * Block * Configuration-group	**13.418**	**1.754**	**0.048**	**0.071**
Context * Block * Load * Configuration-group	13.418	1.415	0.148	0.058
Error(Context * Block)	308.620			
Between subjects				
Load	**1**	**28.991**	**0.000**	**0.387**
Configuration-group	2	1.137	0.330	0.047
Load * Configuration-group	2	1.187	0.314	0.049
Error	46			

Computed using alpha = .05

Table C26

Mixed Analysis of Variance for Workload Effects on Number of Dwells between Phase 1 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	1	1.172	0.293	0.061
Context * Transfer Condition	1	0.021	0.887	0.001
Context * Configuration-group	2	3.037	0.073	0.252
Context * Transfer Condition * Configuration-group	2	1.257	0.308	0.123
Error(Context)	18			
Block	**6.066**	**5.208**	**0.000**	**0.224**
Block * Transfer Condition	6.066	0.412	0.872	0.022
Block * Configuration-group	12.133	0.596	0.843	0.062
Block * Transfer Condition * Configuration-group	12.133	0.978	0.475	0.098
Error(Block)	109.197			
Context * Block	14	0.958	0.497	0.051
Context * Block * Transfer Condition	14	0.723	0.751	0.039
Context * Block * Configuration-group	28	1.168	0.263	0.115
Context * Block * Transfer Condition * Configuration-group	28	0.688	0.882	0.071
Error(Context * Block)	252			
Between subjects				
Transfer Condition	1	0.725	0.406	0.039
Configuration-group	2	0.138	0.872	0.015
Transfer Condition * Configuration-group	2	1.658	0.218	0.156
Error	18			

Computed using alpha = .05

Table C27

Mixed Analysis of Variance for Transfer Condition Effects on Number of Re-dwells between Phase 1 Dual-Single and Dual-Dual Transfer Conditions

Source	df	F	Sig.	*η*
Within subjects				
Context	1	0.036	0.850	0.002
Context * Transfer Condition	1	3.221	0.086	0.128
Context * Configuration-group	2	1.275	0.299	0.104
Context * Transfer Condition * Configuration-group	2	0.265	0.769	0.024
Error(Context)	22			
Block	**4.271**	**12.111**	**0.000**	**0.355**
Block * Transfer Condition	4.271	2.119	0.080	0.088
Block * Configuration-group	8.543	0.625	0.765	0.054
Block * Transfer Condition * Configuration-group	8.543	0.611	0.777	0.053
Error(Block)	93.969			
Context * Block	5.655	1.488	0.191	0.063
Context * Block * Transfer Condition	5.655	1.124	0.352	0.049
*Context * Block * Configuration-group*	*11.310*	*1.746*	*0.069*	*0.137*
Context * Block * Transfer Condition * Configuration-group	11.310	1.176	0.310	0.097
Error(Context * Block)	124.407			
Between subjects				
Transfer Condition	1	0.001	0.977	0.000
Configuration-group	2	1.377	0.273	0.111
Transfer Condition * Configuration-group	2	0.068	0.934	0.006
Error	22			

Computed using alpha = .05

Table C28

Mixed Analysis of Variance for Transfer Effects on Number of Re-dwells between Phase 2 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**8.357**	**0.010**	**0.317**
Context * Transfer Condition	1	0.986	0.334	0.052
Context * Configuration-group	2	1.117	0.349	0.110
Context * Transfer Condition * Configuration-group	2	1.903	0.178	0.175
Error(Context)	18			
Block	**5.187**	**1.086**	**0.374**	**0.057**
Block * Transfer Condition	5.187	0.687	0.640	0.037
Block * Configuration-group	10.374	0.746	0.684	0.077
Block * Transfer Condition * Configuration-group	10.374	0.821	0.613	0.084
Error(Block)	93.366			
Context * Block	5.211	1.005	0.421	0.053
Context * Block * Transfer Condition	5.211	1.267	0.284	0.066
Context * Block * Configuration-group	10.422	0.805	0.629	0.082
Context * Block * Transfer Condition * Configuration-group	10.422	0.877	0.561	0.089
Error(Context * Block)	93.801			
Between subjects				
Transfer Condition	**1**	**7.352**	**0.014**	**0.290**
Configuration-group	2	0.741	0.491	0.076
Transfer Condition * Configuration-group	**2**	**3.574**	**0.049**	**0.284**
Error	18			

Computed using alpha = .05

Table C29
Mixed Analysis of Variance for Transfer Effects on Number of Re-dwells between Phase 2 Dual-Single and Single-Single Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	1	3.103	0.093	0.134
Context * Transfer Condition	1	0.621	0.440	0.030
Context * Configuration-group	2	1.911	0.174	0.160
Context * Transfer Condition * Configuration-group	2	1.734	0.202	0.148
Error(Context)	20			
Block	5.703	1.392	0.226	0.065
Block * Transfer Condition	5.703	1.264	0.281	0.059
Block * Configuration-group	11.406	1.117	0.354	0.101
Block * Transfer Condition * Configuration-group	11.406	1.063	0.397	0.096
Error(Block)	114.059			
Context * Block	5.061	0.474	0.797	0.023
Context * Block * Transfer Condition	5.061	1.227	0.302	0.058
Context * Block * Configuration-group	10.122	0.686	0.737	0.064
Context * Block * Transfer Condition * Configuration-group	10.122	0.555	0.849	0.053
Error(Context * Block)	101.223			
Between subjects				
Transfer Condition	1	0.467	0.502	0.023
Configuration-group	2	0.417	0.665	0.040
Transfer Condition * Configuration-group	2	1.391	0.272	0.122
Error	20			

Computed using alpha = .05

Table C30
Mixed Analysis of Variance on Trial Response Time

Source	df	F	Sig.	*η*
	Within subjects			
Context	**1**	**266.652**	**0.000**	**0.870**
Context * Transfer Condition	3	1.526	0.222	0.103
Context * Configuration-group	2	1.708	0.194	0.079
Context * Transfer Condition * Configuration-group	6	0.701	0.650	0.095
Error(Context)	40			
Epoch	**3.467**	**48.219**	**0.000**	**0.547**
Epoch * Transfer Condition	10.402	1.608	0.107	0.108
Epoch * Configuration-group	6.935	1.103	0.365	0.052
Epoch * Transfer Condition * Configuration-group	20.804	1.064	0.393	0.138
Error(Epoch)	138.694			
Context * Epoch	**5**	**7.780**	**0.000**	**0.163**
Context * Epoch * Transfer Condition	15	0.865	0.604	0.061
Context * Epoch * Configuration-group	10	0.661	0.759	0.032
Context * Epoch * Transfer Condition * Configuration-group	30	1.141	0.291	0.146
Error(Context * Epoch)	200			
	Between subjects			
Transfer Condition	**3**	**4.561**	**0.008**	**0.255**
Configuration-group	2	1.208	0.309	0.057
Transfer Condition * Configuration-group	6	0.259	0.953	0.037
Error	40			

Computed using alpha = .05

Table C31
Mixed Analysis of Variance for Workload Effects on Dwell Durations

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**316.323**	**0.000**	**0.873**
Context * Load	1	1.715	0.197	0.036
Context * Configuration-group	2	2.034	0.142	0.081
Context * Load * Configuration-group	2	0.117	0.890	0.005
Error(Context)	46			
Epoch	**1.730**	**48.215**	**0.000**	**0.512**
Epoch * Load	1.730	0.803	0.436	0.017
Epoch * Configuration-group	3.460	0.699	0.575	0.029
Epoch * Load * Configuration-group	3.460	1.673	0.172	0.068
Error(Epoch)	79.583			
Context * Epoch	**2**	**18.983**	**0.000**	**0.292**
Context * Epoch * Load	2	0.581	0.561	0.012
Context * Epoch * Configuration-group	4	1.076	0.373	0.045
Context * Epoch * Load * Configuration-group	**4**	**2.642**	**0.039**	**0.103**
Error(Context * Epoch)	92			
Between subjects				
Load	**1**	**19.157**	**0.000**	**0.294**
Configuration-group	2	1.126	0.333	0.047
Load * Configuration-group	2	0.303	0.740	0.013
Error	46			

Computed using alpha = .05

Table C32

Mixed Analysis of Variance for Workload Effects on Dwell Durations between Phase 1 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**122.583**	**0.000**	**0.872**
Context * Transfer Condition	1	1.057	0.318	0.055
Context * Configuration-group	2	0.624	0.547	0.065
Context * Transfer Condition * Configuration-group	2	1.887	0.180	0.173
Error(Context)	18			
Epoch	**2**	**23.164**	**0.000**	**0.563**
Epoch * Transfer Condition	2	1.985	0.152	0.099
Epoch * Configuration-group	4	0.333	0.854	0.036
Epoch * Transfer Condition * Configuration-group	4	0.256	0.904	0.028
Error(Epoch)	36			
Context * Epoch	**2**	**10.145**	**0.000**	**0.360**
Context * Epoch * Transfer Condition	2	2.312	0.114	0.114
Context * Epoch * Configuration-group	4	1.817	0.147	0.168
Context * Epoch * Transfer Condition * Configuration-group	4	0.633	0.642	0.066
Error(Context * Epoch)	36			
Between subjects				
Transfer Condition	1	0.470	0.502	0.025
Configuration-group	2	0.073	0.930	0.008
Transfer Condition * Configuration-group	2	0.144	0.867	0.016
Error	18			

Computed using alpha = .05

Table C33
Mixed Analysis of Variance for Workload Effects on Dwell Durations between Phase 1 Dual-Single and Dual-Dual Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**206.066**	**0.000**	**0.904**
Context * Transfer Condition	1	0.632	0.435	0.028
Context * Configuration-group	2	1.278	0.299	0.104
Context * Transfer Condition * Configuration-group	2	0.419	0.663	0.037
Error(Context)	22			
Epoch	**1.731**	**21.546**	**0.000**	**0.495**
Epoch * Transfer Condition	1.731	0.617	0.523	0.027
Epoch * Configuration-group	3.462	2.014	0.120	0.155
Epoch * Transfer Condition * Configuration-group	3.462	0.247	0.887	0.022
Error(Epoch)	38.083			
Context * Epoch	**2**	**7.917**	**0.001**	**0.265**
Context * Epoch * Transfer Condition	2	0.184	0.833	0.008
Context * Epoch * Configuration-group	4	1.418	0.244	0.114
Context * Epoch * Transfer Condition * Configuration-group	4	1.195	0.326	0.098
Error(Context * Epoch)	44			
Between subjects				
Transfer Condition	1	0.644	0.431	0.028
Configuration-group	2	1.548	0.235	0.123
Transfer Condition * Configuration-group	2	0.025	0.975	0.002
Error	22			

Computed using alpha = .05

Table C34
Mixed Analysis of Variance for Transfer Effects on NSIs between Phase 2 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	*η*
Within subjects				
Context	**1**	**76.558**	**0.000**	**0.810**
Context * Transfer Condition	1	1.075	0.314	0.056
Context * Configuration-group	2	0.893	0.427	0.090
Context * Transfer Condition * Configuration-group	2	0.528	0.599	0.055
Error(Context)	18			
Epoch	1.253	2.804	0.101	0.135
Epoch * Transfer Condition	1.253	0.380	0.591	0.021
Epoch * Configuration-group	2.506	0.487	0.662	0.051
Epoch * Transfer Condition * Configuration-group	2.506	1.356	0.281	0.131
Error(Epoch)	22.555			
Context * Epoch	2	1.336	0.276	0.069
Context * Epoch * Transfer Condition	2	0.148	0.863	0.008
Context * Epoch * Configuration-group	4	0.297	0.878	0.032
Context * Epoch * Transfer Condition * Configuration-group	4	1.691	0.173	0.158
Error(Context * Epoch)	36			
Between subjects				
Transfer Condition	1	3.221	0.090	0.152
Configuration-group	2	0.831	0.452	0.085
Transfer Condition * Configuration-group	2	0.677	0.520	0.070
Error	18			

Computed using alpha = .05

Table C35

Mixed Analysis of Variance for Transfer Effects on Number of Re-dwells between Phase 2 Dual-Single and Single-Single Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**70.836**	**0.000**	**0.780**
Context * Transfer Condition	1	3.293	0.085	0.141
Context * Configuration-group	2	1.676	0.212	0.144
Context * Transfer Condition * Configuration-group	2	0.265	0.770	0.026
Error(Context)	20			
Epoch	2	1.171	0.320	0.055
Epoch * Transfer Condition	2	1.799	0.179	0.083
Epoch * Configuration-group	4	2.210	0.085	0.181
Epoch * Transfer Condition * Configuration-group	4	0.708	0.591	0.066
Error(Epoch)	40			
Context * Epoch	2	2.685	0.081	0.118
Context * Epoch * Transfer Condition	2	0.347	0.709	0.017
Context * Epoch * Configuration-group	4	0.748	0.565	0.070
Context * Epoch * Transfer Condition * Configuration-group	4	0.530	0.715	0.050
Error(Context * Epoch)	40			
Between subjects				
Transfer Condition	**1**	**8.491**	**0.009**	**0.298**
Configuration-group	2	1.133	0.342	0.102
Transfer Condition * Configuration-group	2	0.334	0.720	0.032
Error	20			

Computed using alpha = .05

Table C36

Mixed Analysis of Variance on Dwell Durations from Experiment 3

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**9.856**	**0.003**	**0.198**
Context * Transfer Condition	3	1.559	0.214	0.105
Context * Configuration-group	2	0.635	0.535	0.031
Context * Transfer Condition * Configuration-group	6	0.279	0.944	0.040
Error(Context)	40			
Block	7.079	0.963	0.459	0.024
Block * Transfer Condition	**21.236**	**5.839**	**0.000**	**0.305**
Block * Configuration-group	14.157	0.742	0.732	0.036
Block * Transfer Condition * Configuration-group	42.472	0.967	0.535	0.127
Error(Block)	283.149			
Context * Block	13.527	0.705	0.765	0.017
Context * Block * Transfer Condition	40.581	1.125	0.279	0.078
Context * Block * Configuration-group	27.054	1.095	0.339	0.052
Context * Block * Transfer Condition * Configuration-group	81.162	0.857	0.804	0.114
Error(Context * Block)	541.082			
Between subjects				
Transfer Condition	**3**	**4.097**	**0.013**	**0.235**
Configuration-group	2	1.412	0.256	0.066
Transfer Condition * Configuration-group	6	1.131	0.362	0.145
Error	40			

Computed using alpha = .05

Table C37
Mixed Analysis of Variance for Workload Effects on Dwell Durations

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**3.952**	**0.053**	**0.079**
Context * Load	1	0.029	0.865	0.001
Context * Configuration-group	2	0.339	0.714	0.015
Context * Load * Configuration-group	2	1.222	0.304	0.050
Error(Context)	46			
Block	5.403	1.753	0.117	0.037
Block * Load	**5.403**	**2.842**	**0.014**	**0.058**
Block * Configuration-group	10.806	0.600	0.825	0.025
Block * Load * Configuration-group	10.806	0.930	0.511	0.039
Error(Block)	248.547			
Context * Block	8.477	0.853	0.562	0.018
Context * Block * Load	8.477	1.336	0.220	0.028
Context * Block * Configuration-group	16.954	1.190	0.269	0.049
Context * Block * Load * Configuration-group	16.954	0.923	0.547	0.039
Error(Context * Block)	389.944			
Between subjects				
Load	**1**	**20.657**	**0.000**	**0.310**
Configuration-group	2	2.234	0.119	0.089
Load * Configuration-group	2	1.147	0.326	0.048
Error	46			

Computed using alpha = .05

Table C38

Mixed Analysis of Variance for Workload Effects on Dwell Durations between Phase 1 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	*η*
Within subjects				
Context	1	1.242	0.280	0.065
Context * Transfer Condition	1	0.500	0.489	0.027
Context * Configuration-group	2	0.355	0.706	0.038
Context * Transfer Condition * Configuration-group	2	0.031	0.970	0.003
Error(Context)	18			
Block	5.679	2.137	0.059	0.106
Block * Transfer Condition	5.679	0.736	0.614	0.039
Block * Configuration-group	11.358	0.974	0.476	0.098
Block * Transfer Condition * Configuration-group	11.358	0.731	0.711	0.075
Error(Block)	102.220			
Context * Block	14	1.701	0.056	0.086
Context * Block * Transfer Condition	14	0.775	0.696	0.041
Context * Block * Configuration-group	28	1.356	0.116	0.131
Context * Block * Transfer Condition * Configuration-group	28	1.334	0.128	0.129
Error(Context * Block)	252			
Between subjects				
Transfer Condition	1	0.700	0.414	0.037
Configuration-group	2	0.258	0.776	0.028
Transfer Condition * Configuration-group	2	0.188	0.830	0.020
Error	18			

Computed using alpha = .05

Table C39

Mixed Analysis of Variance for WorkTransfer Condition Effects on Dwell Durations between Phase 1 Dual-Single and Dual-Dual Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	1	2.299	0.144	0.095
Context * Transfer Condition	1	0.085	0.773	0.004
Context * Configuration-group	2	1.026	0.375	0.085
Context * Transfer Condition * Configuration-group	2	0.032	0.969	0.003
Error(Context)	22			
Block	**4.849**	**2.385**	**0.045**	**0.098**
Block * Transfer Condition	4.849	0.485	0.781	0.022
Block * Configuration-group	9.699	0.732	0.688	0.062
Block * Transfer Condition * Configuration-group	9.699	1.138	0.342	0.094
Error(Block)	106.688			
Context * Block	6.828	1.053	0.397	0.046
Context * Block * Transfer Condition	6.828	1.299	0.255	0.056
Context * Block * Configuration-group	13.656	0.969	0.486	0.081
Context * Block * Transfer Condition * Configuration-group	13.656	0.701	0.767	0.060
Error(Context * Block)	150.218			
Between subjects				
Transfer Condition	1	0.002	0.967	0.000
Configuration-group	2	2.105	0.146	0.161
Transfer Condition * Configuration-group	2	1.771	0.194	0.139
Error	22			

Computed using alpha = .05

Table C40

Mixed Analysis of Variance for Transfer Effects on Dwell Durations between Phase 2 Single-Single and Single-Dual Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**9.982**	**0.005**	**0.357**
Context * Transfer Condition	1	1.689	0.210	0.086
Context * Configuration-group	2	0.722	0.499	0.074
Context * Transfer Condition * Configuration-group	2	0.370	0.696	0.039
Error(Context)	18			
Block	4.072	1.041	0.393	0.055
Block * Transfer Condition	4.072	1.226	0.307	0.064
Block * Configuration-group	8.143	1.191	0.316	0.117
Block * Transfer Condition * Configuration-group	8.143	0.911	0.514	0.092
Error(Block)	73.289			
Context * Block	6.013	0.881	0.512	0.047
Context * Block * Transfer Condition	6.013	0.688	0.660	0.037
Context * Block * Configuration-group	12.025	1.366	0.193	0.132
Context * Block * Transfer Condition * Configuration-group	12.025	1.101	0.367	0.109
Error(Context * Block)	108.226			
Between subjects				
Transfer Condition	**1**	**16.965**	**0.001**	**0.485**
Configuration-group	2	0.189	0.829	0.021
Transfer Condition * Configuration-group	2	0.972	0.397	0.097
Error	18			

Computed using alpha = .05

Table C41

Mixed Analysis of Variance for Transfer Effects on Number of Re-dwells between Phase 2 Dual-Single and Single-Single Transfer Conditions

Source	df	F	Sig.	η
Within subjects				
Context	**1**	**4.654**	**0.043**	**0.189**
Context * Transfer Condition	**1**	**5.615**	**0.028**	**0.219**
Context * Configuration-group	2	0.909	0.419	0.083
Context * Transfer Condition * Configuration-group	2	0.556	0.582	0.053
Error(Context)	20			
Block	4.931	0.912	0.475	0.044
Block * Transfer Condition	4.931	0.364	0.870	0.018
Block * Configuration-group	9.862	1.343	0.219	0.118
Block * Transfer Condition * Configuration-group	9.862	1.400	0.192	0.123
Error(Block)	98.624			
Context * Block	14	1.192	0.281	0.056
Context * Block * Transfer Condition	14	1.531	0.099	0.071
Context * Block * Configuration-group	28	0.862	0.670	0.079
Context * Block * Transfer Condition * Configuration-group	28	1.177	0.251	0.105
Error(Context * Block)	280			
Between subjects				
Transfer Condition	1	0.436	0.516	0.021
Configuration-group	2	0.874	0.433	0.080
Transfer Condition * Configuration-group	2	0.164	0.850	0.016
Error	20			

Computed using alpha = .05

8. Appendix D: Experiment Software

The experiment software is located at http://www.cogsci.rpi.edu/cogworks and is maintained by the CogWorks Laboratory.

9. Appendix E: Experiment Materials

All participant materials (e.g., instructions, blank informed consent forms, and debriefing statements) for each experiment can be found at http://www.cogsci.rpi.edu/cogworks and is maintained by the CogWorks Laboratory.