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Learning Routine Visual Search Sequences

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LEARNING ROUTINE VISUAL SEARCH SEQUENCES

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Abstract

Learning Routine Visual Search Sequences

Monique D. Crouse

Searching through a series of environments is a pervasive everyday experience and although visual search and sequence learning are long researched fields, little is known about people's ability to learn a visual search sequence. Environments that require more visual search may disrupt sequence learning, for a multitude of reasons. They require more effort, time, and, if people were learning a sequence of eye movements, they would increase the noise to signal ratio. However, some visual search environments may permit sequence learning. In particular, when people search a familiar context of distractors, they can more quickly find the target than when searching a novel context. This dissertation investigated the impact of visual search demands (i.e. popout vs non-popout targets) and distractor environment (i.e. static vs consistently changing contexts vs random distractors) on sequence learning. The results show that sequence learning occurred in all conditions, suggesting that random noise in the environment and the need to perform visual search does not interfere with sequence learning. This finding has implications for understanding the mechanisms of sequence learning as well as implications for the everyday world. When people interact with user interfaces, they often engage in the same sequence of actions. These findings show that sequence learning occurs in a variety of cases and suggest that when user interface updates and items are no longer where and when users expect them, people will likely struggle to complete their tasks.

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Chapter 1: Introduction

People perform many routine visual searches throughout their day. They search for items in their home such as their watch and keys on their way to work. They also routinely search for clickable elements on their computer or phone when looking for a file or uploading a photo to social media. Traditional theories of how attention is guided during visual search have focused on two mechanisms; bottom-up involuntary processes, where attention is drawn to unique (aka salient) features, and top-down voluntary processes, where attention is drawn to goal relevant locations and features. However, attention can also be guided by past experiences with environmental regularities in a manner that is neither top-down nor bottom-up (Awh et al., 2012).

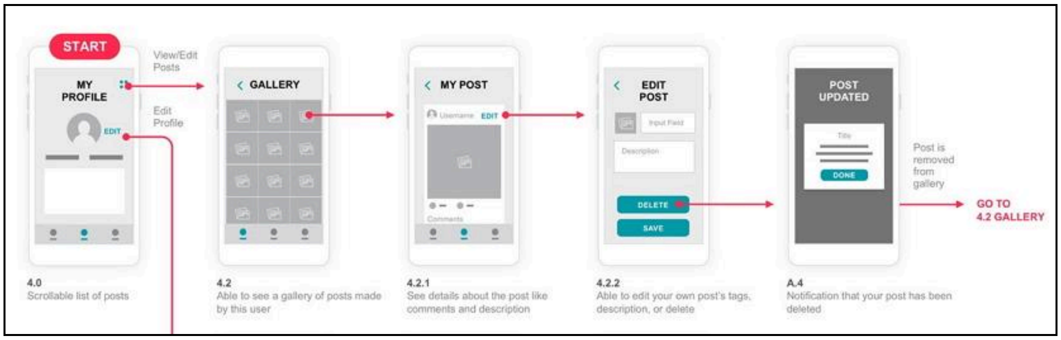
Environmental regularities can bias attention to features and locations even when a stimulus's physical attributes remain the same (equivalent salience). For example, even though your keys or a desktop icon look the same, your attention becomes biased to look for these items in the locations you expect and with the features you expect. Unlike goal driven attention, these biases are implicit and involuntary; people are often unaware of the regularity and people continue to be guided by the expectations even when they are in opposition to a person's goals. (Jiang et al., 2013; Jiang et al., 2014). You may stay up all night repeatedly searching for your remote in your couch cushions but ultimately find it on the dining room table. Violations in expectations lead to slower performance (Chun & Jiang, 1998; Nissen & Bullemer, 1987) and sometimes gaps in visual awareness and memory

(Droll et al., 2005; Moyes, 1994). More often than not though, these expectations are beneficial and they allow people to complete tasks more quickly. For example, people become faster at finding a target if it often appears in a particular location (i.e. Spatial Probability Cueing; Jiang et al., 2013). People are also faster at visually searching for a target when it appears in a previously searched configuration of distractors (searching for a T among Ls) compared to a novel configuration (i.e. Contextual Cueing; Chun & Jiang, 1998).

Environmental regularities can also occur as a repeating sequence over time. For example, people often move through a sequence of search contexts when using phone apps, websites and other user interfaces. This sequence can most easily be seen through a user flow diagram such as the one in Figure 1 where a user sees several different screens when uploading a photo to social media. However, sequence learning is studied almost exclusively with sparse environments and with targets that have sudden onsets; these kinds of environments do not require visual search. The typical task used to assess sequence learning is the Serial Reaction Time (SRT) Task where there are four horizontally located possible locations a stimulus could appear, and people are faster at responding when the stimulus location follows a repeating sequence compared to a random sequence (Nissen & Bullemer, 1987).

Figure 1

Depiction Of User Flow In Social Media App



Note. Image from mockplus.com blog “Top 25 User Flow Tools & Templates for Smooth UX”

The SRT task was recently adapted into a T among Ls visual search task by Toh, Remington, & Lee (2021). The target T appeared in one of the four screen quadrants among 12 distractor Ls. The target was an easy to find popout target (white T among black Ls). The distractors stayed in the same static locations throughout the experiment. The location of the T followed a repeating 12-trial sequence. Similar to the typical SRT task, Toh and colleagues found participants’ reaction time (RT) became faster as they repeatedly completed the 12-trial sequences but when the sequence was disrupted and the target appeared in random locations, their RT was significantly slower. Toh et al. (2021) tested sequence learning under multiple conditions to replicate and expand on the SRT task, see Table 1. Relevant to the current study is their experiment 3 (described above) and experiments 4 and 5. In these later two experiments the distractors changed randomly trial-to-trial and had a popout (exp. 4) or non-popout (exp. 5) target. In these experiments with random distractors, Toh et al. (2021) found no evidence of sequence learning. However, Toh et al.’s (2021) study leaves open the question of whether the target must popout and whether the distractors must be static in order for sequence learning to occur.

Table 1

Summary of Toh et al. (2021)

Exp#	Popout vs non popout	Distractor Type	Sub experiment (1a, 1b, etc.)	Sequence Learning
1	Popout	Placeholders	Horizontal vs four connors	Yes
2	Popout and N/A	Placeholders and none	Placeholders vs none	Yes
3	Popout	Static	T at or not at meridians	Yes
4	Popout	Random	T at or not at meridians	No
5	Nonpopout	Random	N/A	No
6	Popout	Static, Block 11 random	T at or not at meridians	N/A

Table 1. Summary of Toh et al. (2021) experiments.

When a target does not pop-out, people usually need to search through multiple distractors before they find the target (aka serial search). Serial visual search, compared to pop-out search, often requires more eye movements, time, and effort; these factors may reduce or eliminate learning a target location sequence. However, visual search is facilitated by environmental regularities such as the contextual cueing effect where people are faster at finding a target in familiar contexts compared to unfamiliar ones (Chun & Jiang, 1998). Visual search through a familiar sequence of search contexts may be one kind of environment where distractors could change trial-to-trial and lead to target location sequence learning. The everyday world is dynamic but rarely completely random; it often contains predictable changes. Whether a context sequence could facilitate learning a visual search sequence is unknown. Therefore, this dissertation will investigate the impact of popout vs non-popout (i.e. serial search) and the impact of different search environments: specifically static distractors, distractors that follow a sequence of search contexts, and randomly changing distractors on target location sequence learning.

Sequence Learning

To understand and predict how visual search demands may impact sequence learning we need to first address the mechanisms of sequence learning. For example, if participants are learning a sequence of eye movements, then looking through many distractors when performing serial search would create noise in the sequence signal of eye movements. However, if participants are learning a sequence of target stimuli locations, then intervening eye movement noise would not disrupt sequence learning. Moreover, if participants are learning the sequence of response buttons, then visual variability such as changing distractor locations should minimally impact sequence learning. This all taps into one of the main questions in sequence learning literature regarding how a learned sequence is represented.

Not all factors involved in executing a sequence are represented and thus not required to stay the same for performance to stay similarly facilitated. For example, SRT sequence learning is effector independent meaning sequence learning is intact when a person switches from using four fingers to using a single “hunt and peck” finger (Cohen et al., 1990). Rather than learning a sequence of motor movements, participants learned a sequence of response locations or the spatial endpoints of motor movements in egocentric (i.e. body relative) space, which do not change when someone uses a different finger (Willingham et al., 2000).

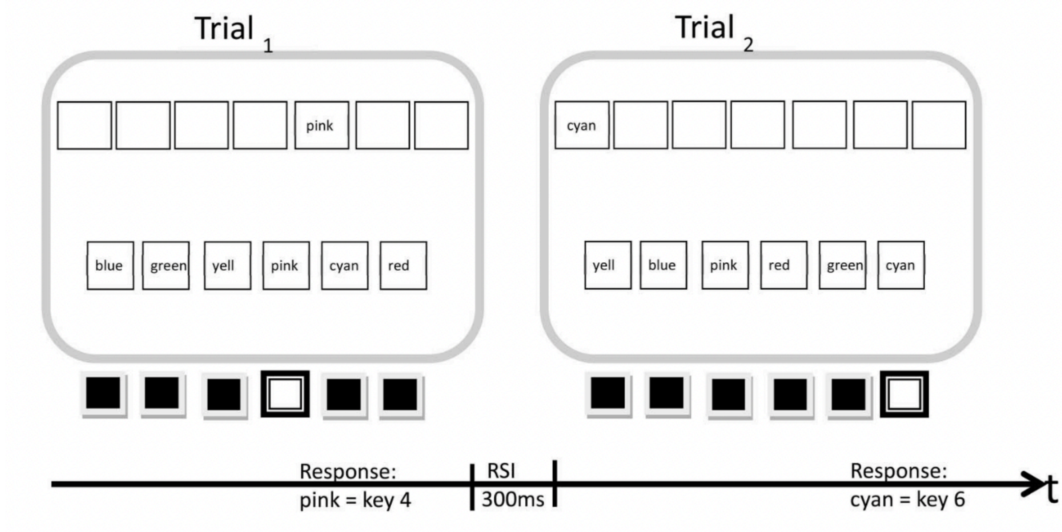
Whether people can learn a sequence of target locations in visuomotor tasks like the SRT task was a greatly debated issue in SRT literature. While several visual statistical learning studies show that people can learn a sequence of stimulus features such as shapes and colors (Higuchi et al., 2016; Musz et al., 2014; Eitam, et al., 2013; Zhao et al., 2013), evidence of learning of a sequence of stimuli locations was elusive. Willingham, et al., (1989) and Mayr (1996) addressed this issue with seemingly conflicting results. To disentangle learning a target location sequence from learning a response sequence, they asked participants to respond to stimuli features (color or shape, respectively) and, in some conditions, target stimuli appeared in a predictable sequence of locations. Sequence learning was assessed by the typical SRT task disruption measure that shows slower performance when there is an unlearned or random sequence compared to when there is the learned sequence. Willingham et al., (1989) did not find sequence learning for a sequence of stimulus locations whereas Mayr (1996) did find sequence learning for a sequence of stimuli locations. Mayr argued the close proximity of stimuli and highly salient colors in Willingham and colleagues' (1989) experiment downplayed the usefulness of spatial information. However, the main criticism of Mayr's (1996) work is that the greater distance in stimuli caused sequence learning to be learned via eye movements rather than the sequence of stimuli (Schwarb & Schumacher, 2012). Sequence learning in Toh and colleagues's (2021) visual search study may have been based on learned eye movements from one target location to the next rather than on the visual sequence of target locations. This mechanism may mean that sequence learning would be weaker or not possible when the target must be searched for with many random eye movements.

The conflicting results and debate on target location sequence learning can be disambiguated by the Dual-system model of sequence learning, (Keele et al., 2003; see also Eberhardt et al., 2017). This account uses a multilevel approach to sequence learning and consists of unidimensional and multidimensional systems. In the unidimensional system, multiple sequences can be learned in parallel as long as they are in different dimensions. Although, what constitutes a dimension is left somewhat vague, the concept of dimensions seems to align with the theory of Event Coding (Hommel, 2004) which argues that a motor action simultaneously activates corresponding perceptual representations and vice versa. This definition means that learning response locations would interfere with learning stimulus locations. In this case, both rely on the spatial (i.e. location) dimension. In SRT tasks (and many everyday procedural tasks) the to-be-learned visual sequence is a sequence of stimuli locations and learning a sequence of response locations (to press each button in a typical SRT task) would hinder learning the sequence of stimuli locations.

This framework of sequence learning is supported by a study by Eberhardt et al., (2017) who showed that one cannot simultaneously learn a location-based response sequence and a location-based stimulus sequence. To assess this they created a paradigm where the response button locations and stimuli locations are uncorrelated, see Figure 2. A color square appeared in the top row and participants pressed the button (bottom row) corresponding to the color squares in the middle row. Critically, the order of the middle row changed each trial, thus the stimulus location (top row) could follow a sequence uncorrelated to the location sequence of the response buttons in the bottom row. They found that a stimulus-location sequence can be learned concurrently with a response-color identity sequence (evident by slower RT when the stimulus location sequence was random) but participants showed no learning of a stimulus-location sequence when concurrent with a response-location sequence. Instead, participants only learned the response-location sequence. Mayr (1996) was able to find location based learning (either from learning stimuli locations or eye movements) because the response sequence was correlated with a shape sequence. Thus, rather than both the visual stimulus sequence and response sequence learning relying on location, the response sequence could be represented by a shape identity sequence, freeing location based sequence learning available for learning stimuli locations or eye movements.

Figure 2

The Paradigm Used In Eberhardt Et Al., (2017)



Note. Participants pressed a button in the bottom row that spatially corresponded to the button in the middle row that matched the color in the top row. Middle row of colored boxes would change each trial making the sequence of button response locations random.

Willingham et al. (1989) also assessed stimulus location sequence learning with a color response but, unlike Mayr (1996), they did not show target location sequence learning. The reason for this discrepancy may be because responses in Willingham et al. (1989) were based on response locations. In Eberhardt et al.'s (2017) third experiment, they showed that how responses are coded impacts what sequence learning can occur (see also: Gaschler et al., 2012). They provided participants with either color instructions "if the stimulus is blue, press the blue response button" or response location instructions "if the stimulus is blue, press the left most response button." They found only the color instruction participants were able to learn the stimuli location sequence. The reasoning was that because responses were based on the color dimension, the spatial dimension was free to learn the stimuli location sequence. These findings suggest responses in Willingham et al. (1989) may have been coded as response locations even though participants were reacting to colored stimuli. In their experiment, participants were specifically trained to respond to particularly located buttons for each color stimulus.

Furthermore, the response sequence in Willingham et al. (1989) was random and random response locations may have interfered with learning the stimuli location sequence. This issue is not always the case though; target location sequence learning was found in Eberhardt et al. (2017) when the response sequence was random. Perhaps this is because in their study the responses to stimuli were not tied to particular locations (if the target was pink, in one trial participants would press the leftmost button but in another trial would press the rightmost button and this mapping was given to them each trial whereas in Willingham et al. (1989) blue always meant press the leftmost button) perhaps the need to remember these spatial relationships interfered with target location sequence learning. Whether random spatial noise disrupts sequence learning is unclear but if sequence learning relies on a single resource pool then spatial noise should interfere with learning a spatial sequence. Toh and colleagues' (2021) found that there was no evidence of sequence learning in a visual search task when the distractors changed location trial-to-trial even though the response sequence was still present and participants still executed the same finger movements. Perhaps the spatial nature of a visual search task and need to move one's eyes, disrupted participants' ability to learn spatial sequences (sequence of target locations or sequence of button presses). Additionally, this finding occurred with both popout and non-poutout search. The popout search may have minimized random eye movements but multiple factors may be at play. For example, in a completely random environment why would one expect the target to follow consistent rules. Taken together, the SRT literature suggests that there is a single resource pool to learn location based sequences. People cannot learn two location based sequences and they seem to be unable to learn a location based sequence when there is location based randomness such as the need to make random eye movements during visual search. However, the number of eye movements needed to find a target varies based on the search environment.

Visual Search: Popout Vs Serial Search

In search environments like Toh et al. (2021) where there is a white T among black Ls, the target has a unique feature that can quickly guide attention via the bottom-up salient signal. This feature search is characterized by essentially optimal guidance that is independent of the number of distractors (Wolfe, 2021). Visual search guidance is often measured via a RT by distractor regression. This slope measurement is not a direct measure of the number of distractors inspected but related to the cost in RT with additional distractors. In perfectly guided search, the RT by distractor slope would be 0 ms/distractor, meaning no increase in RT for more distractors. In feature search, the slope is effectively zero and in these search environments, the target is found quickly, efficiently, and with minimal if any search through distractors (Wolfe, 2021). In an eye tracker study, where a target was white among black tilted lines, the target was found with one saccade regardless of the target's eccentricity from the center of the search area (Scialfa & Joffe, 1998). The popout target in Toh et al.

(2021) could quickly grab participants' attention would have enabled participants to learn a sequence of eye movements rather than target locations.

In more complex environments, people must perform serial search through multiple distractors before the target is found; on average, about half of a search environment will be inspected before a target is found (Wolfe, 2021). There are multiple kinds of search environments and Wolfe's guided search model describes a spectrum of more or less guided search depending on the environment and one's past experiences (Wolfe, 2021). For a T among L search task where the target is defined by the relationship between features (e.g. horizontal and vertical lines either making an L or an T), the RT by distractor search slope is 20-40 ms/distractor (Wolfe, 2021). This suggests people perform some amount of serial search before the target is found. This random search may interfere with learning a sequence of target locations.

***Demands of Serial Visual Search Beyond Eye Movement*s**

The increased time needed to find a target among distractors, in and of itself, might impact sequence learning. The typical SRT task uses response to stimulus intervals (RSI) that are less than a second (500ms, Nissen & Bullemer, 1987, 200ms, Reed & Johnson, 1994; 300ms, Eberhardt et al. 2017). Frensch and Miner, (1994) found evidence of weaker sequence learning when there was a 1500ms RSI compared to a 500ms RSI. However, Destrebecqz and Cleeremans (2003) found a similar magnitude of sequence learning when there was a 0ms, 250ms, and 1500ms RSIs. The discrepancy between Frensch and Miner, (1994) and Destrebecqz and Cleeremans (2003) may be due to various methodological differences between the two studies; for example, they used different types of sequences and different lengths of sequences. Of note, however, is that Destrebecqz and Cleeremans (2003) found evidence of explicit knowledge for participants with 250ms and 1500ms RSIs but not for 0ms RSIs. Perhaps a serial search task might result in weaker sequence learning or may result in similar sequence learning but with more participants explicitly aware of the sequence. Since the sequences used in this dissertation are more similar to Destrebecqz and Cleeremans (2003), we may find more explicit knowledge for participants in non-popout conditions that require longer search time compared to participants with popout search.

Another possible aspect of visual search that might interfere with learning a target location sequence could be the greater mental effort required to search for a target in more complex environments. A greater amount of time to find a target does not necessarily mean greater search effort is required. However, a recent study showed that participants will exert physical effort (gripping a device) to reduce the number of distractors. Participants exert more force to remove distractors in large set size displays suggesting that effort scales with visual search demands (Anderson & Lee, 2023). This could mean that needing to serially search a display might increase participants' mental effort or cognitive load and disrupt sequence learning.

The question of whether sequence learning is disrupted by cognitive load is commonly assessed with a tone-counting (i.e. dual-task) SRT task (Nissen & Bullemer, 1987). In addition to the SRT task, participants hear either a high or low pitched tone during the interval between sequence elements and participants keep a running total of high-pitched tones. Sequence learning is reduced when participants must perform this secondary task compared to when just performing the single SRT task (Jiménez & Vázquez, 2005). A main contributor to this disruption is thought to be the disruption in sequence structure rather than cognitive load. Stadler (1995) found that inserting longer RSIs (400ms rather than 0ms) at the same rate as when high tones would have occurred produced similar disruptions in sequence learning as the tone-counting task. Thus, sequence learning in a visual search task might not be disrupted by the increased task load but perhaps disrupted by variability in response time (finding some targets faster than other targets). Sequence learning in dual-task scenarios seems to be based on the ability to integrate the two tasks into one regular sequence, where the secondary task predicts the SRT task (Jiménez & Vázquez, 2005; Rah et al., 2000; Schmidtke & Heuer, 1997). Perhaps a SRT task could be integrated with a visual search task if the eye movements were regular but not if the eye movements were random.

The various aspects related to serial search (i.e. eye movements, time, effort) might interfere with sequence learning; however, a study that had a target identity sequence (number identities) suggests that people can learn this sequence during a visual search task (Jiménez, & Vázquez, 2011). Participants searched for an even number (e.g. 8) among seven odd numbers that were all the same value (e.g. all 3s). The ~1000 ms search time suggests participants were performing serial search yet there was still evidence of sequence learning. This study suggests that sequence learning is not disrupted by visual search, in general, but whether people could learn a sequence of target locations during sequential visual search is unclear. The spatial nature of visual search tasks may uniquely interfere with learning location-based sequences. However, environments that provide more attentional guidance and reduce the need to visually search a display may facilitate learning a sequence of target locations.

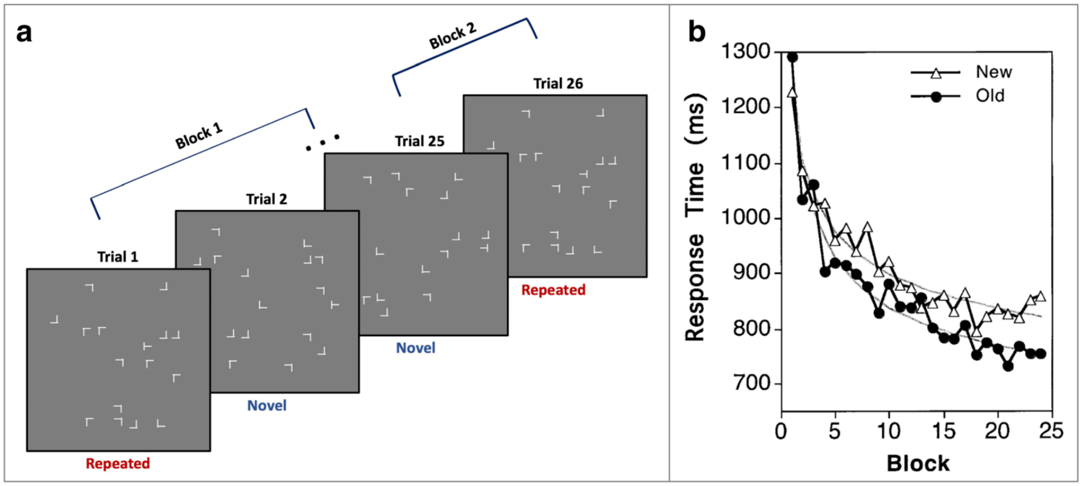
Visually searching the same environment repeatedly can allow people to become familiar with that environment and more quickly find a target. In a repeat search task (Solman & Smilek, 2010), participants searched the exact same environment repeatedly for particular letters among several unique letters. Participants learned where the different letters were located and more quickly found each target letter when requested. The number of accurate first saccades increased in the repeat condition but not in a condition with a randomly changing environment. However, this type of guidance could only partially be applied to an environment where the target is a variably located T among static Ls. The location of the distractors stays consistent but, unlike the repeat search task, participants cannot learn a particular location for a particular letter. At most they might be better at identifying and rejecting distractors. However, a different form of guidance called contextual cueing is when people become familiar with several different repeated distractor contexts and a particular context guides attention to a particular target location.

Contextual Cueing

One of many ways one's past experiences with an environment can guide visual search is through the contextual cueing effect where people are faster to find a target in a familiar environment compared to a novel one. The effect was coined by Chun and Jiang, (1998) in a paper that assessed how a configuration of distractor Ls could facilitate visual search for a target T in repeated contexts compared to novel contexts (see Figure 3). The study controlled for an overall spatial bias to one particular location by making the target equally likely to appear in all possible locations for both repeat and novel contexts. Thus, the context itself facilitated search for the location of the target in that context. In a recent methodological paper by Jiang and Sisk, (2019), the standard search for a T among Ls produces a contextual cueing effect after 5-8 repetitions with RTs that are 50-100ms faster in repeated contexts compared to novel contexts. In the two decades between their original paper and this methodological paper, there were over 100 studies investigating the contextual cueing effect. One reason why there might be so many studies about contextual cueing is that the effect likely relies on multiple mechanisms (Goujon et al., 2015) and results can change depending on the task and stimuli. There seem to be two main mechanisms, one that is based on a global association between target and context and one that is based on eye movement habits and local relationships. These two different types of contextual cueing guidance mechanisms may differently impact learning of a target location sequence. The more eye movement based mechanism may tax spatial resources to some extent but the global association mechanism might act more like a feature cue.

Figure 3

Depiction Of Typical Contextual Cueing Experiment



Note. Image taken from Sisk et al., (2019).

Eye Movement Based Contextual Cueing

Chun and Jiang's (1998) original paper proposed that contextual cueing is due to an association between the context and the target. However, in a more recent review, Jiang (2017) suggested the contextual cueing effect is due to habits in how a scene is visually searched. Both mechanisms may be present to some extent in the typical T among Ls search. However, this type of search seems to encourage a contextual cueing effect that is narrow in focus and based on how one's eyes move from one distractor to the next. Conversely, change detection tasks, where people monitor a global area, encourages more global contextual cueing (Jiang & Song, 2005). The contextual cueing effect also did not transfer when the same configuration that was learned with a visual search task was later used in a change detection task. For the reverse direction, learning with a change detection task showed only partial transfer when later presented as a visual search task. This minimal transfer in learning between task types suggests that performance in these tasks is based on two different mechanisms (Jiang & Song, 2005). Furthermore, the type of contextual cueing can depend on whether people are able to move their eyes. When participants are required to maintain central fixation, they learn the global configuration of distractors; however, when participants' eyes were free to move, they learn the relationship between the target and nearby distractors (Zinchenko et al., 2020). Additionally, distractors far from the target can randomly change without impacting the contextual cuing effect (Olson, & Chun, 2002) indicating participants do not learn target location based on a whole global configuration association.

A familiar context can also reduce (but not eliminate) visual search demands. The contextual cueing effect is associated with a reduction in the number of eye movements and a more efficient scan path to the target. One way this reduction occurs is due to greater number of first saccades to the target in familiar environments compared to novel environments (Peterson & Kramer, 2001). However, these first saccades comprise a small proportion of trials (11.3%) and the main contextual cueing facilitation seems to be due to a shortening of the random exploratory phase of the search and an earlier start of a direct search phase where each saccade brings the target closer (Tseng & Li, 2004; Manginelli & Pollmann, 2009, Zhao et al. 2012). In trials where the first saccade did not go to the target, there were still fewer fixations (Peterson & Kramer, 2001). The reduction in eye movements seem to particularly be due to fewer inefficient eye movements away from the target (which accounted for 72% of the reduction in total number of saccades), compared to little reduction in efficient fixations toward the target (which accounted for 28% of the reduction in total number of saccades) (Zhao et al. 2012). The contextual cueing effect when one searches for a T among Ls seems to be largely based on some search through the configuration of distractors for context recognition and then an efficient search to the target.

The presence of a small amount of search in a familiar environment before recognition accounts for a lack of evidence for a consistent reduction in the traditional visual search metric of measuring guidance via a decreased RT by set size search slope. In other words, the difference in search time between a set size of 12 vs 8 visual search task should be smaller with repeat contexts because attention should be more efficiently guided to the target and there should be less impact of additional distractors compared to search with novel contexts. However, Wolfe and colleagues (2007) only found a small decrease in search slopes for familiar compared to novel contexts (Kunar et al. 2007). The important aspect to remember, though, is the contextual cueing effect (specifically the type with non-popout search for a T among Ls) only occasionally impacts first saccades and is based on how the context is searched rather than the global configuration; some amount of search occurs before context recognition. Consequently this type of guidance would have a weak effect on search slope (Sisk et al., 2019; Harris & Remington, 2020). Thus, search slope is a misleading measure for guidance in contextual cueing studies. The debate on whether a component of the contextual cueing effect is due to response facilitation may continue (Sisk et al., 2019) but evidence from eye tracking studies indicate the effect benefits attentional guidance and reduces the number of random exploratory eye movements.

A visual search/eye movement based contextual cueing mechanism may weakly support sequence learning. The contextual cueing effect in this kind of environment seems to be based on learned visual search and results in fewer eye movements, particularly random exploratory eye movements, that may provide enough of a consistent learnable sequence to support sequence learning. This learning may be weaker than that found with an environment that has static distractors and a popout target due to the increased demands of visual search. However, learning might not be completely abolished as it is when there is a completely random changing environment. Unfortunately, previous studies left vague if contextual cueing results in a more efficient scan path or more consistent scan path. Whether a sequence of search contexts with a non-popout target can support sequence learning is unclear.

Contextual Cueing With Popout And Global Configuration Learning

The contextual cueing effect is typically studied with non-popout search environments; however, a much smaller effect can occur with popout targets (12ms; Geyer et al., 2010; 14ms; Harris & Remington, 2017). The smaller effect is likely due to a RT floor effect and the limited room for RT to decrease between the familiar and novel contexts. Similarly, there is a very small but significant reduction in eye movements (0.05 fixations per trial) in familiar contexts with a popout target compared to novel contexts (Harris & Remington, 2017). In general, a popout target can be found with one saccade (Scialfa & Joffe, 1998). The minimal search required with popout search is similar to the previously mentioned tasks that required minimal or no eye movements (Jiang & Song, 2005; Zinchenko et al. 2020). In line with these studies, the contextual cueing effect with a popout target seems to be based on the global configuration. Specifically, when the global configuration repeats there is a contextual cueing effect but there is no evidence of an effect when only the local context repeats (Ogawa & Kumada, 2008). Global association based contextual cueing also occurs with natural scene backgrounds (Rosenbaum & Jiang, 2013) and more abstract backgrounds like fractals (Goujon et al., 2012). How the global configuration is processed when participants search for a popout T among Ls is unclear but it may be like a global shape feature or environmental texture feature like fractals. A feature like cue may enhance sequence learning above and beyond popout search without a sequence of contexts. This enhancement would be from there being two possible sequences that could be learned and facilitate RT (sequence of target locations and sequence of context features). Learning both of these sequences may further speed RT compared to when there is only a sequence of target locations in a static search environment with a popout target.

Learning a location based sequence and a feature based sequence is cross-dimensional learning and is supported by Keele's Dual-system account by the multidimensional system (Keele et al., 2003). Unlike the unidimensional system which learns regularities in a single dimension, the multidimensional system learns regularities across dimensions. For example, participants can learn regularities between auditory and visual stimuli. In a dual-task SRT task, participants responded to both types of stimuli and when stimuli in one sequence predicted stimuli in the other, participants had faster RT compared to when the auditory stimuli were random (Schmidtke, & Heuer, 1997). Multidimensional learning often has a larger effect on RT (~150ms) compared to single dimension learning (~65ms), (Keele et al., 2003). Not only is the effect larger, but the effect on RT is greater than the sum of RT effects for two single dimensional learning. Alternatively, when two sequence regularities are present but uncorrelated to each other, the impact when both are disrupted is the sum of when either is disrupted alone (Mayr, 1996). Thus, learning a sequence of target locations when this is also correlated with a sequence of feature contexts may have even greater benefit to RT compared to an environment with static distractors.

When multiple kinds of environmental regularities are present, sometimes only one type of regularity is learned (Endo, & Takeda, 2004; Kunar et al., 2014). Potentially, contextual cueing or target location sequence learning could overshadow learning the other. However, Jiménez and Vázquez (2011) showed that participants can learn a sequence of response identities and learn repeat contexts (i.e. contextual cueing). This finding suggests that contextual cueing does not prevent sequence learning or vice versa, at least with a sequence of target identities. Critically, in their study, the contexts did not follow any sequence (or correlate or predict the sequence of response identities) so whether people can learn a sequence of visual search contexts and the effect they have on target location sequence learning is unknown.

Current Study

The experiments in this dissertation consisted of 6 between subject conditions made of 2 target conditions and 3 distractor conditions. The target conditions either had a popout target (white T among black Ls) or did not have a popout target (black T among black Ls). The distractor conditions were either static and exactly the same throughout the experiment, were changing via a sequence of search context where each target is paired with a unique search context, or were randomly changing location and orientation each trial. In all conditions the target followed a 12 trial location sequence that repeats 3 times per block. In the 11th block, the target locations were an unlearned sequence. In the 12th block, the repeating sequences resumed. For the condition with a context sequence, the target location and the context sequence were paired such that both the target location and the distractor context were reordered to the new unlearned sequence, thus neither were predictive of the next trial but each context was still predictive of its paired target location. For simplicity, the following dissertation is presented as three experiments each with a pop-out and non-popout target sub-experiments. Experiment 1 has distractors that are static (Experiment 1a and 1b), Experiment 2 has changing context sequence (Experiment 2a and 2b) and Experiment 3 are randomly changing distractors (Experiment 3a and 3b) However, since all conditions were conducted concurrently, we can compare across all conditions.

Sample Size Justification

Sample size calculation will be based on the disruption effect in Toh et al. (2021) experiment 4A with a non-popout target and static distractors. Using Doug Bonett's R function for required sample size for paired sample t-test with power of 0.8 and assuming there is at least 0.6 correlation between the two RT measures, the required sample size is 20 participants. This number is also consistent with previous literature. All the experiments in Toh et al. had a sample size of 16 participants. SRT studies that use SOC sequences (see methods for description) have slightly greater sample size (N=20, Reed & Johnson, 1994; N= 22, Eberhardt et al. 2017). Data was collected until all conditions had at least 20 participants. The key planned analysis was for a paired sample t-test comparing how RT is different at two time points, however, after data collection a better assessment was realized which was a one-sample t-test on the difference in RT for each participant. Additionally, this effect of interest (disruption effect) is defined by an increase in RT, therefore all t-tests of this effect are one-tailed t-tests. These changes should only increase statistical power and are not an issue with the collected sample size.

Participants

All studies in this dissertation were run concurrently. Each participant was assigned one of the six conditions in the following way, participant 1 participated in Experiment 1a, participant 2 in Experiment 1b, participant 3 in Experiment 2a, etc. With six conditions, this pattern repeated every 6 participants. Participants were

UCSC students from the Sona subject pool. Two participants were removed due to failure to understand and follow instructions.

Measures of Sequence Learning: General Methods

Sequence learning was assessed with three types of measures. The first measure will be referred to as the *learning effect*. This measure assesses learning benefits throughout the experiment session and measures the change in RT over the course of the first 10 blocks. Faster reaction time as the experiment continues could reflect becoming better at the task in general, learning how to search through the distractors, or learning the sequence of target locations. While a significant decrease in RT cannot tell us what participants were learning, it indicates they learned something. The relationship between RT and log of block was investigated using a mixed regression model. Block was fixed and a within subjects factor, participants were included as a random effect (random slopes and intercepts). The log of block was used because doing so provided a better model fit than using block alone. Accuracy based learning effect was also assessed to identify possible speed accuracy trade offs and was analyzed in the same way as the RT disruption effect.

The second measure will be referred to as the *disruption effect*. This measure is the typical measure of sequence learning which compares the average RT in blocks 10 and 12 to the RT in block 11. Block 11 was when participants experienced an unlearned target location sequence. If participants learned and came to expect the target to follow the repeating sequence of locations, they would be slower to respond when there is an unlearned sequence and there is a violation of these expectations.

Because this effect predicts an increase in RT, a one-tailed t-test will be used. Also, rather than assessing differences in average performance, changes in RT were directly assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12. Accuracy based disruption effect was also assessed to identify possible speed accuracy trade offs and was analyzed in the same way as the RT disruption effect.

Sequence learning was also assessed by explicit awareness. Participants were asked an explicit recognition question: “While completing the previous search tasks, did the locations of where the T appeared ever occur in a repeating sequence?” The above question did not specify that the repeating sequence was a 12 item sequence so participants might have been indicating that they were aware of more simple transition patterns. However, if participants were aware of any pattern, they could exert conscious effort to learn all or part of the sequence, making sequence learning more likely. Explicit sequence knowledge was also assessed with a generation task where participants were shown the location of the T on the first trial then asked to indicate the quadrant of the T for the following 11 trials in the sequence. Accuracy was based on these 11 trials and defined by absolute position, for example, if the 6th position did not match the 6th position in the learned sequence that trial was marked as incorrect.

Chapter 2: Experiment 1

Experiment 1a, Static Distractors With Popout

Methods

Materials.

The experiment was created with Psychopy (Peirce et al., 2019) and presented on a Mac. Participants were seated approximately 56 cm (22.05 in) in front of a computer monitor with a 23 in (58.42 cm). display using 1920 x 1080 resolution. All stimuli were presented on a gray background (RGB 128, 128, 128). Ls were black (RGB 0, 0 ,0) and the T were white (RGB 255, 255, 255). In each visual search context there was one target T and twelve distractor Ls. Both letters were 1.3 degrees of visual angle (DVA). The Ls had a small offset of 0.92 DVA. The orientation of the T changed each trial and was randomly selected from one of four orientations (0°, 90°, 180°, or 270°) and appeared in each orientation equally often. The orientation of the Ls were randomly selected from these orientations and remained the same throughout the experiment. The visual search area 48.97 DVA X 28.79 DVA was divided into an invisible 11 x 11 grid with 2.95 DVA of empty space between the monitor edges and the search area. The vertical and horizontal center column and row were clear of search stimuli and only contain a faint gray (RGB 102, 102, 102) cross that was 2.61 DVA at the center of the grid. Search stimuli appeared in the remaining four 5 x 5 grid quadrants. The center location of each letter was jittered between 0 and 0.5 DVAs.

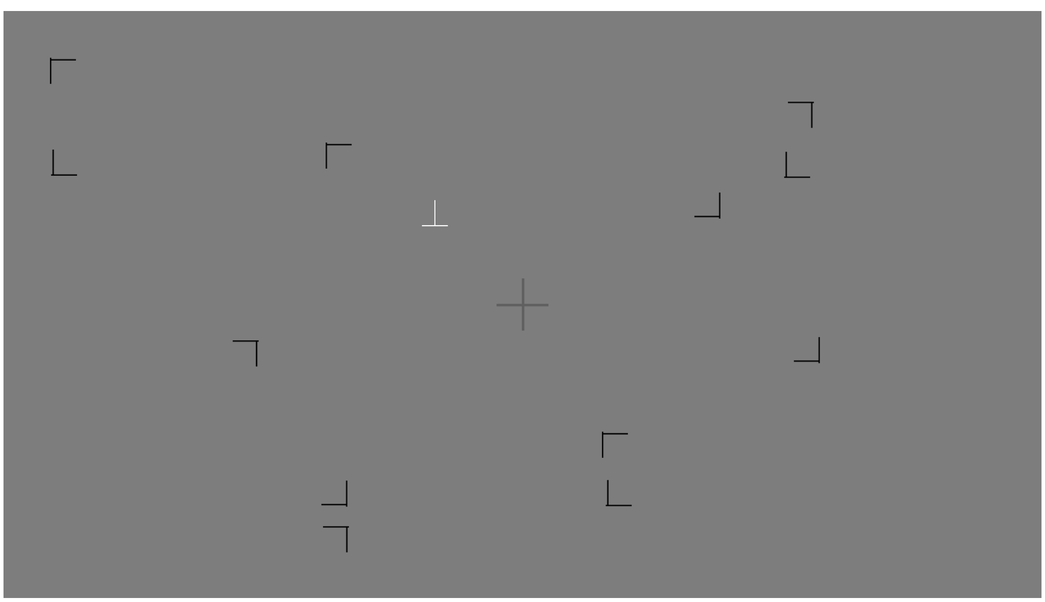
The distractor display was randomly generated at the start of the experiment with the constraint that there were three distractors per quadrant. The distractors stayed in the same static locations throughout the experiment. The location of the target followed a repeating 12-trial sequence. All participants experienced the following sequence of target locations 1, 4, 3, 2, 4, 1, 3, 1, 2, 3, 4, 2 in which each number corresponds to one of the screen quadrants. This sequence is a second order conditional (SOC) sequence (Reed & Johnson, 1994) and follows several rules. Each location occurs equally often (3 times); each location occurs every 4 to 5 trials; each transition occurs equally often (1 to 2, 4 to 3, etc.) thus two locations are needed to predict the third ensuring people are learning sequence and not transition probabilities. Additionally, the sequence contains a single reversal 1, 3, 1 at position six. Any 12 element sequence that is made up of four unique items will have one reversal. Having these features and keeping them consistent between the learned and unlearned blocks is critical because SRT tasks that use randomly generated sequences can show a difference in reaction time unrelated to sequence learning and could be due to, for example, the learned sequence having more reversals and being easier to execute than the unlearned sequence.

During the unlearned block, participants experienced three different sequences that are different from the learned sequence, these are 2, 4, 3, 1, 4, 2, 3, 2, 1, 3, 4, 1 and 3, 2, 1, 4, 2, 3, 1, 3, 4, 1, 2, 4 and 1, 3, 4, 2, 3, 1, 4, 1, 2, 4, 3, 2. They are all SOC sequences with a reversal at position six, meaning any possible mental chunking of the sequences at the reversal was the same across sequences. What makes these sequences different from the learned sequence and each other was the content of the sequence. The value at each location was different from the same position in another sequence, for example, the value at position 2 in one sequence was different from the value in position 2 in another sequence. By extension this difference also means they all also had unique reversals. Although there were some instances where the sequences share triplet values, they all had unique Quadruplets (4 item length sequences).

Participants indicated the location of the target T using the keyboard by pressing the D and C keys with their left hand for targets in the left top and bottom quarters of the screen, respectively and by pressing the J and N keys with their right hand for targets in the right top and bottom quarters of the screen, respectively. An example of a search environment is shown in Figure 4.

Figure 4

Example Of The Visual Search Array



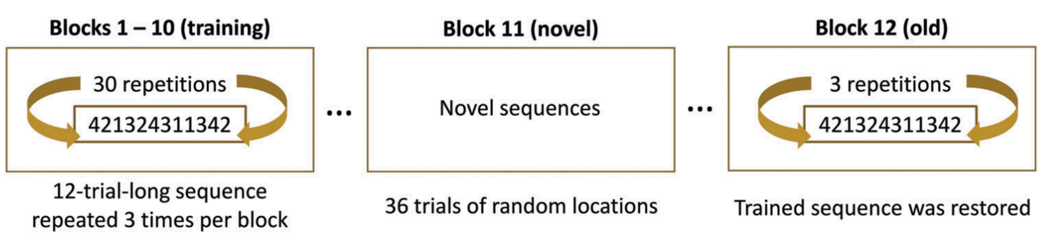
Note. Half of participants saw a white T and the other half saw a black T

Procedure.

Participants were instructed to search for a target T among Ls. Participants completed 8 practice trials where the location of the target was random. During the rest of the experiment, unbeknownst to the participants, the target location followed a repeating 12-trial sequence. The sequence repeated three times per block for 10 blocks, (i.e. 30 repetitions of the 12-trial sequence). There were a total of 12 blocks. In the 11th block, the targets followed unlearned SOC sequences (2, 4, 3, 1, 4, 2, 3, 2, 1, 3, 4, 1 and 3, 2, 1, 4, 2, 3, 1, 3, 4, 1, 2, 4 and 1, 3, 4, 2, 3, 1, 4, 1, 2, 4, 3, 2), every participant saw the sequences in this order. Doing this with these sequences maintained the low level regularities between sequences. In the last (12th) block the sequence returned to the learned sequence present in the first 10 blocks (see Figure 5).

Figure 5

Procedure Diagram From Toh et al. (2021)



Note. This main pattern is also used in the current dissertation however the sequences were all SOC sequences.

At the end of the experiment, participants were asked a recognition question and performed a generation task. Participants were asked, “While completing the previous search tasks, did the locations of where the T appeared ever occur in a repeating sequence?" Then participants performed a generation task which was one sequence of the 12 trial learned sequence but with the target absent from the 2nd through 12th trial trials. Participants were asked to indicate what quadrant they thought the target would appear. Chance performance would be indicated by 25% accuracy. Participants then completed a survey for basic demographic information (handedness, age, etc).

Results and Discussion

Reaction time data was filtered to remove incorrect responses (4.73% of all trials) and trials with slow RT (1.37% of all trials). Slow trials were defined within each participant; trials were removed if they were slower than 3 SDs from that participant's average RT. These filters resulted in a total removal of 5.66% of trials (some trials fit multiple filters). These trials were not removed from accuracy data to fully assess proportion correct. Subjects were then removed from analysis if their RT or accuracy during the first 9 blocks was greater than 2 SDs from study average. Two participants were removed by this filter: one participant's RT was 3.52 SD from study mean RT and another participant's accuracy was -2.69 SD from the study mean accuracy. Of the remaining 22 participants, fifteen participants identified as female, six identified as male, one identified as non-binary. Participants' ages ranged between 17 to 25 years old (M = 19.50 years old, SD = 1.68 years old).

In general, RT was within the range expected for visual search with popout (M = 457.72 ms, SD = 80.61 ms). The learning effect was assessed over the course of the first 10 blocks, see Figure 6a. There was a significant negative correlation between

RT and block, $r(218) = -.30$, $p < .001$, 95% CI [-.41, -.17]. The mixed regression model showed a significant negative relationship between RT and the log of block count (□ = -52.29 ms, SE = 10.34 ms, 95% CI [-72.68 ms, -31.91 ms], $t(197) = -5.06$, $p < .001$). These results indicate that participants had learned something during the first 10 blocks of the study and were able to respond faster as the experiment progressed. Accuracy was also assessed for possible speed accuracy trade off. Accuracy was quite high overall ($M = 95.65\%$, $SD = 2.76\%$). Accuracy and block were not significantly correlated, $r(218) = -.10$, $p = .16$, 95% CI [-.22, .04]. These results indicate that participants' accuracy did not detectably increase or decrease as the experiment went on and also that the RT learning effect was not due to a speed accuracy trade off.

The disruption effect was assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12, see Figure 6b. The average RT increase ($M = 51.83$ ms; $SD = 39.58$ ms) was significantly different from zero, $t(21)$ 6.14, $p < .0001$, CI [37.31, Inf]. This finding suggests that people can learn a sequence of target locations when the target is a popout and the distractors are static. The change in accuracy was also assessed for an accuracy based disruption effect. The average accuracy change ($M = -3.03\%$; $SD = 6.83\%$) was significantly different from zero, $t(21)$ -2.08, $p = .05$, CI [-6.06, -0.004]. This finding shows that there was a small but significant decrease in accuracy when participants experienced the unlearned sequence in block 11. Both accuracy and RT were negatively affected suggesting that there was not a speed accuracy trade off for the disruption effect.

Participants were also asked if they thought the T ever followed a repeating sequence. Fifty five percent of participants answered "yes." Participant's accuracy on the generation task ($M = 26.86\%$; $SD = 14.71\%$) was not significantly different from chance (25%), $t(21) = 0.59$, $p = .56$, 95% CI [20.34%, 33.38%], see Figure 6c. This finding indicates that although participants reported being aware of some repeating pattern, they were unable to produce the sequence themselves. This single study lacks the sample size needed to compare the learning and disruption effects between those who indicated being aware and being unaware, but see Chapter 5 for a cross experiment analysis addressing this question.

These results indicate that when the target is a popout and can be found quickly, then people can learn a repeating sequence of target locations. This finding replicates Toh et al.'s (2021) experiment 3 results and extends the finding to more complex sequences. By using an SOC sequence, these results indicate that people are learning a sequence of 3 or more elements, rather than the simple and easier to learn transition probabilities that were present in Toh and colleagues' sequences.

Experiment 1b, Static Distractors With A Non-Popout Target

Methods

Experimental 1b was the same as Experiment 1a, except that the target T was black, the same color as the distractor Ls (i.e. non-popout).

Results and Discussion

Reaction time data was filtered to remove incorrect responses (5.12% of all trials) and trials with slow RT (1.84% of all trials). Slow trials were defined within each participant; trials were removed if they were slower than 3 SDs from that participant's average RT. These filters resulted in a total removal of 6.77% of trials (some trials fit multiple filters). These trials were not removed from accuracy data to fully assess proportion correct. Subjects were then removed from analysis if their RT or accuracy during the first 9 blocks was greater than 2 SDs from study average. One participant was removed by this filter for their RT being 3.23 SD from study mean RT. Of the remaining 21 participants, eighteen participants identified as female, three identified as male, zero identified as non-binary. Participants' ages ranged between 18 to 23 years old ($M = 20.00$ years old, $SD = 1.34$ years old).

In general, RT was within the range expected for visual search with a non-popout target ($M = 1395.06$ ms, $SD = 300.62$ ms). The learning effect was assessed over the course of the first 10 blocks, see Figure 6a. There was a significant negative correlation between RT and block, $r(208) = -.50$, $p < .001$, 95% CI [-.60, -.40]. The mixed regression model showed a significant negative relationship between RT and the log of block count (□ = -314.39 ms, $SE = 38.46$ ms, 95% CI [-390.25 ms, -238.53 ms], $t(188) = -8.18$, $p < .001$). These results indicate that participants had learned something during the first 10 blocks of the study and were able to respond faster. Accuracy was also assessed for possible speed accuracy trade off. Accuracy again was quite high (M = 94.70%, SD = 3.53%). There was a significant negative correlation between accuracy and block, r(208) = -.20, p = .003, 95% CI [-.33, -.07]. The mixed regression model showed a significant negative relationship between accuracy and log of block count (□ = -1.44%, SE = 0.66%, 95% CI [-2.75%, -0.13%], t(188) = -2.17, p = .03). These results indicate that participants' accuracy decreased as the experiment went on, perhaps due to fatigue and/or perhaps due to a speed accuracy trade-off. Thus, the learning effect in RT could be due at least in part to multiple factors, but the key finding is that there was a significant learning effect and that this could be at least in part due to sequence learning.

The typical measure of sequence learning was assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12, see Figure 6b. The average RT increase (M = 125.80 ms; SD = 216.13 ms), was significantly different from zero, t(20) 2.67, p =.007, CI [44.46, Inf]. This finding suggests that people can learn a sequence of target locations when the target is a non-popout and the distractors are static.

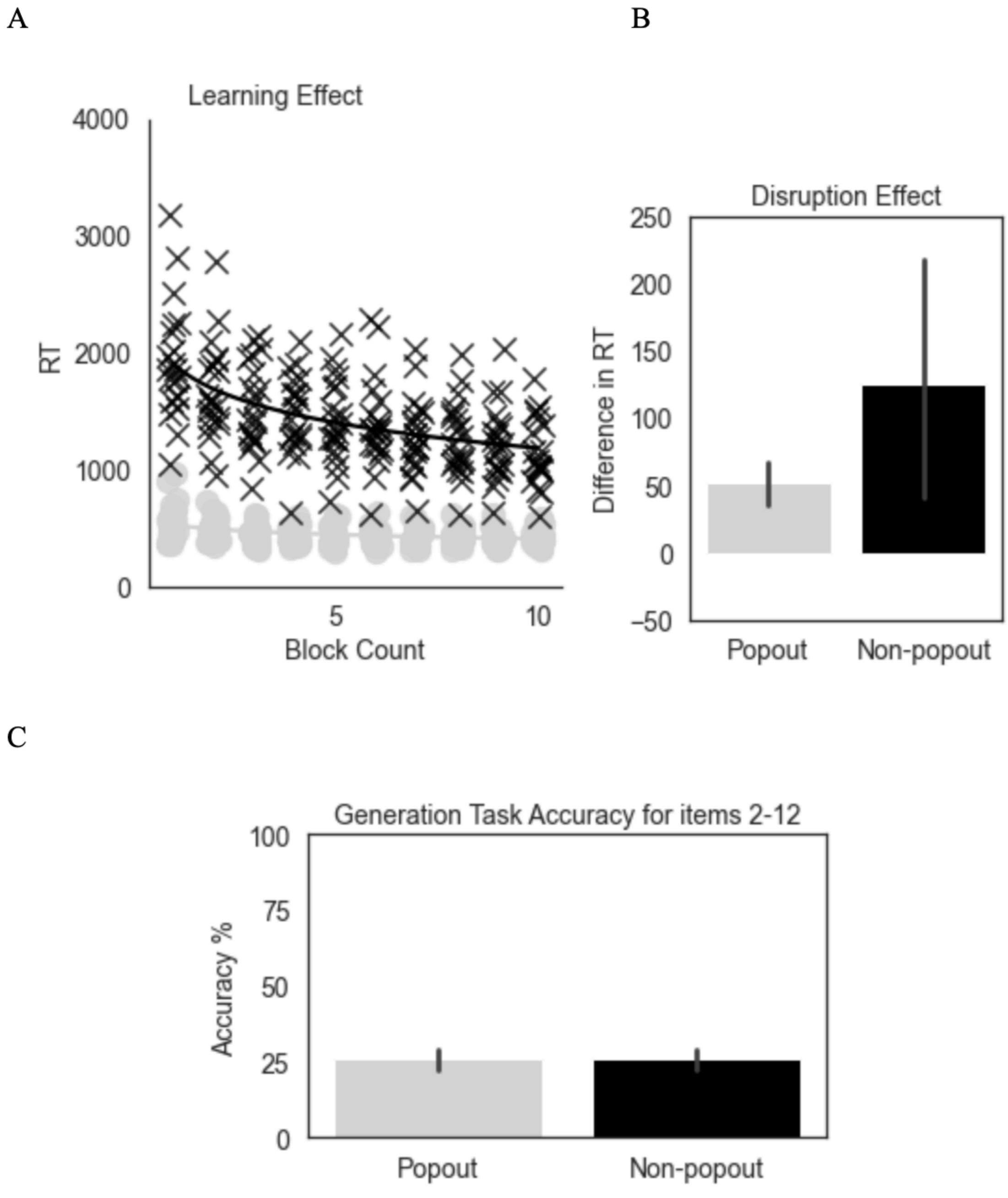
The change in accuracy was also assessed for these last three blocks for an accuracy based disruption effect. The average accuracy change (M = -1.39%; SD = 4.77%), was not significantly different from zero t(20) -1.33, p = .20, CI [-3.56, 0.78]. These results did not show evidence of a change in accuracy when participants experienced the unlearned sequence in block 11. If there really is no difference, then this would suggest that there was not a speed accuracy trade off for the disruption effect.

Participants were also asked if they thought the T ever followed a repeating sequence. Fifty seven percent of participants answered “yes.” Participant’s accuracy on the generation task ($M = 26.84\%$; $SD = 13.32\%$) was not significantly different from chance (25%), $t(20) = 0.63$, $p = .53$, 95% CI [20.78, 32.90], see Figure 6c. This finding indicates that although participants reported being aware of some repeating pattern, they were unable to produce the sequence themselves.

These results indicate that when the target is a non-popout and the distractors are static, people can learn a repeating sequence of target locations. This result suggests that sequence learning is possible in environments that require some level of visual search.

Figure 6

Performance With Static Distractors



Note. (A) Learning effect, decrease in RT over the first 10 blocks of Experiments 1a and 1b. Gray circles = popout target (Experiment 1a), black X = non-popout target (Experiment 1b). (B) Disruption effect, difference in RT between block 11 and the average of blocks 10 and 12. Error bars are 95% confidence intervals. (C) Generation task accuracy, with four possible responses, chance is 25%. Error bars are 95% confidence intervals.

Chapter 3: Experiment 2

Experiment 2a, Context Sequence Distractors With Popout

Methods

Experiment 2 was the same as experiment 1a except the search environment changed trial-to-trial and was paired with a target location creating a sequence of distractor contexts (e.i. the context on trial one was the same as the context on trial one of the next repeat, etc).

Results and Discussion

Reaction time data was filtered to remove incorrect responses (7.32% of all trials) and trials with slow RT (1.28% of all trials). Slow trials were defined within each participant; trials were removed if they were slower than 3 SDs from that participant's average RT. These filters resulted in a total removal of 8.15% of trials (some trials fit multiple filters). These trials were not removed from accuracy data to fully assess proportion correct. Subjects were then removed from analysis if their RT or accuracy during the first 9 blocks was greater than 2 SDs from study average. Two participants were removed by this filter: one participant's RT was 2.66 SD from study mean RT and another participant's accuracy was -3.82 SD from the study mean accuracy. Of the remaining 20 participants, seventeen participants identified as female, three identified as male, zero identified as non-binary. Participants' ages ranged between 18 to 21 years old (M = 19.05 years old, SD = 1.10 years old).

In general, RT was within the range expected for visual search with popout ($M = 466.56$ms, $SD = 64.762$ ms). The learning effect was assessed over the course of the first 10 blocks, see Figure 7a. There was a significant negative correlation between RT and block, $r(198) = -.34$, $p < .001$, 95% CI [-.46, -.22]. The mixed regression model showed a significant negative relationship between RT and the log of block count (□ = -52.95 ms, $SE = 7.06$ ms, 95% CI [-66.87 ms, -39.02 ms], $t(179) = -7.50$, $p < .001$). These results indicate that participants had learned something during the first 10 blocks of the study and were able to respond faster. Accuracy was also assessed for possible speed accuracy trade off. Accuracy was quite high ($M = 94.21\%$, $SD = 2.64\%$). There was a significant negative correlation between accuracy and block, $r(198) = -.23$, $p = .001$, 95% CI [-.35, -.09]. A mixed regression model was used, this time with fixed participant slopes because there was not sufficient variation in participant slopes to support a random participant slopes model. The model showed a significant negative relationship between accuracy and the log of block count (□ = -1.71%, $SE = 0.42\%$, 95% CI [-2.53%, -0.89%], $t(179) = -4.10$, $p < .001$). These results indicate that participants' accuracy decreased as the experiment went on, perhaps due to fatigue and/or perhaps due to a speed accuracy trade-off. Thus, the RT learning effect could be due at least in part to multiple factors, but the key finding is that there was a significant learning effect and that this could be at least in part due to sequence learning.

The typical measure of sequence learning was assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12, see

Figure 7b. The average RT increase ($M = 34.95$ ms; $SD = 34.07$ ms), was significantly different from zero, $t(19)$ 4.59, $p = .0001$, CI [21.77, Inf]). This finding suggests that people can learn a sequence of target locations when the target is a popout and the distractors change with a consistent sequence of contexts.

Accuracy based disruption effect was assessed the same as the RT disruption effect. The average accuracy change ($M = -4.31\%$; $SD = 5.12\%$), was significantly different from zero $t(19)$ -3.76, $p = .001$, CI [-6.70, -1.91]. This finding shows that there was a small but significant decrease in accuracy when participants experienced the unlearned sequence in block 11. Both accuracy and RT were negatively affected suggesting that there was not a speed accuracy trade off for the disruption effect.

Participants were also asked if they thought the T ever followed a repeating sequence. Sixty five percent of participants answered "yes." Participant's accuracy on the generation task ($M = 24.55\%$; $SD = 13.87\%$) was not significantly different from chance (25%), $t(19) = -0.15$, $p = .88$, 95% CI [18.06, 31.03], see Figure 7c. This finding indicates that although some participants indicated being aware of a repeating pattern, they were unable to produce the sequence themselves.

These results indicate that when the target is a popout and there is a sequence of consistently changing distractor context people can learn a sequence of target locations. This result counters Toh et al.'s (2021) theory that noise in the environment disrupts sequence learning. Although a consistent sequence of context is not completely random, it is more noisy than static distractors.

Experiment 2b, Context Sequence Distractors With A Non-Popout Target

Methods

Experimental 2b was the same as experiment 2a except that the target T was black, the same color as the distractor Ls (i.e. non-popout).

Results and Discussion

Reaction time data was filtered to remove incorrect responses (8.32% of all trials) and trials with slow RT (1.62% of all trials). Slow trials were defined within each participant; trials were removed if they were slower than 3 SDs from that participant's average RT. These filters resulted in a total removal of 9.75% of trials (some trials fit multiple filters). These trials were not removed from accuracy data to fully assess proportion correct. Subjects were then removed from analysis if their RT or accuracy during the first 9 blocks was greater than 2 SDs from study average. Two participants were removed by this filter: one participant's RT was -3.00 SD from study mean RT and another participant's accuracy was -4.83 SD from the study mean accuracy. Additionally, one participant was removed for having extremely low accuracy in one block, 47.2%. Of the remaining 25 participants, nineteen participants identified as female, six identified as male, zero identified as non-binary. Participants' ages ranged between 18 to 24 years old (M = 19.12 years old, SD = 1.59 years old).

In general, RT was within the range expected for visual search with a non-popout target (M = 1640.67 ms, SD = 211.08 ms). The learning effect was assessed over the course of the first 10 blocks, see Figure 7a. There was a significant negative correlation between RT and block, r(248) = -.56, p < .001, 95% CI [-.64, -.47]. The mixed regression model showed a significant negative relationship between RT and the log of block count (□ = -287.27 ms, SE = 27.42 ms, 95% CI [-341.30 ms, -233.24 ms], t(224) = -10.48, p < .001). These results indicate that participants had learned something during the first 10 blocks of the study and were able to respond faster. Accuracy was also assessed for possible speed accuracy trade off. Accuracy was quite high (M = 94.73%, SD = 3.09%). There was a significant negative correlation between accuracy and block, r(248) = -.21, p = .001, 95% CI [-.32, -.08]. A mixed regression model, with fixed participant slopes, showed a significant negative relationship between accuracy and the log of block count (□ = -1.71%, SE = 0.38%, 95% CI [-2.46%, -0.96%], t(179) = -4.52, p < .001). These results indicate that participants' accuracy decreased as the experiment went on, perhaps due to fatigue and/or perhaps due to a speed accuracy trade-off. Thus, the RT learning effect could be due at least in part to multiple factors but the key finding is that there was a significant learning effect and that this could be at least in part due to sequence learning.

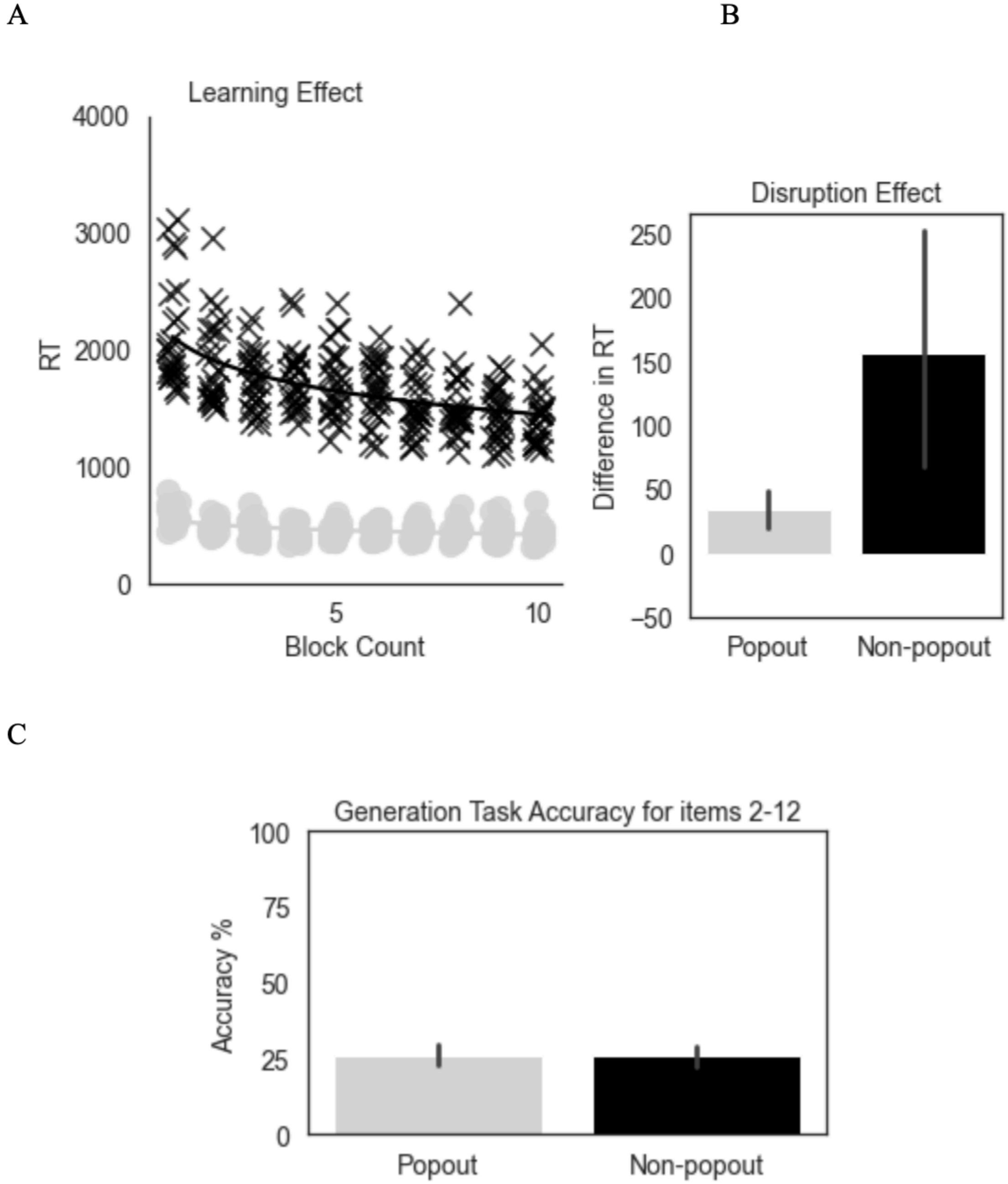
The typical measure of sequence learning was assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12, see Figure 7b. The average RT increase (M = 157.03 ms; SD = 242.14 ms), was significantly different from zero, t(24) 3.24, p = .002, CI [74.17, Inf]). This finding suggests that people can learn a sequence of target locations when the target is a non-popout and the distractors change with a consistent sequence of contexts.

The change in accuracy was also assessed for these last three blocks for an accuracy based disruption effect. Accuracy based disruption effect was assessed the same as the RT disruption effect. The average accuracy change (M = -3.17%; SD = 5.11%), was significantly different from zero t(24) -3.10, p = .005, CI [-5.28, -1.06]. This finding shows that there was a small but significant decrease in accuracy when participants experienced the unlearned sequence in block 11. Both accuracy and RT were negatively affected suggesting that there was not a speed accuracy trade off for the disruption effect.

Participants were also asked if they thought the T ever followed a repeating sequence. Eighty percent of participants answered "yes." Participant's accuracy on the generation task (M = 21.82%; SD = 16.60%) was not significantly different from chance (25%), t(24) = -0.96, p = .35, 95% CI [14.97, 28.67], see Figure 7c. This finding indicates that although some participants reported being aware of a repeating pattern, participants in general were unable to produce the sequence themselves. These results indicate that when the target is a non-popout and there is a sequence of consistently changing distractor context people can learn a sequence of target locations.

Figure 7

Performance With Consistent Distractors



Note. (A) Learning effect, decrease in RT over the first 10 blocks of the Experiments 2a and 2b. Gray circles = popout target (Experiment 2a), black X = non-popout target (Experiment 2b). (B) Disruption effect, difference in RT between block 11 and the average of blocks 10 and 12. Error bars are 95% confidence intervals. (C) generation task accuracy, with four possible responses, chance is 25%. Error bars are 95% confidence intervals.

Chapter 4: Experiment 3

Experiment 3a, Random Distractors With Popout

Methods

Experiment 3 was the same as experiment 2a except all search environments were unique and novel. The target still followed a location sequence but the distractors changed location randomly.

Results and Discussion

Reaction time data was filtered to remove incorrect responses (5.05% of all trials) and trials with slow RT (1.55% of all trials). Slow trials were defined within each participant; trials were removed if they were slower than 3 SDs from that participant's average RT. These filters resulted in a total removal of 5.99% of trials (some trials fit multiple filters). These trials were not removed from accuracy data to fully assess proportion correct. Subjects were then removed from analysis if their RT or accuracy during the first 9 blocks was greater than 2 SDs from study average. Two participants were removed by this filter: one participant's RT was 3.55 SD from study mean RT and another participant's accuracy was -2.45 SD from the study mean accuracy. Of the remaining 23 participants, nineteen participants identified as female, two identified as male, two identified as non-binary. Participants' ages ranged between 18 to 22 years old ($M = 19.74$ years old, $SD = 1.29$ years old).

In general, RT was within the range expected for visual search with a popout target ($M = 546.72$ ms, $SD = 95.69$ ms). The learning effect was assessed over the course of the first 10 blocks, see Figure 8a. There was a significant negative correlation between RT and block, $r(228) = -.34$, $p < .001$, 95% CI [-.45, .22]. The mixed regression model showed a significant negative relationship between RT and the log of block count (□ = -70.16 ms, SE = 11.94 ms, 95% CI [-93.69 ms, -46.62 ms], $t(206) = -5.88$, $p < .001$). These results indicate that participants had learned something during the first 10 blocks of the study and were able to respond faster. Accuracy was also assessed for possible speed accuracy trade off. Accuracy was quite high (M = 95.16%, SD = 2.93%). There was a significant negative correlation between accuracy and block, $r(228) = -.19$, $p = .003$, 95% CI [-.31, -.07]. A mixed regression model showed a significant negative relationship between accuracy and the log of block count (□ = -1.12%, SE = 0.45%, 95% CI [-2.01%, -0.22%], $t(206) = -2.46$, $p = .01$). These results indicate that participants' accuracy decreased as the experiment went on, perhaps due to fatigue and/or perhaps due to a speed accuracy trade-off. Thus, the RT learning effect could be due at least in part to multiple factors but the key finding is that there was a significant learning effect and that this could be at least in part due to sequence learning.

The typical measure of sequence learning was assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12, see Figure 8b. The average RT increase (M = 28.03 ms; SD = 47.60 ms), was significantly different from zero, $t(22)$ 2.82, $p = .005$, CI [10.99, Inf]). This finding suggests that people can learn a sequence of target locations when the target is a popout and the distractors are random.

The change in accuracy was also assessed for these last three blocks for an accuracy based disruption effect. Accuracy based disruption effect was assessed the same as the RT disruption effect. The average accuracy change (M = -1.57%; SD = 5.22%), was not significantly different from zero $t(22)$ -1.44, $p = .16$, CI [-3.83, 0.69]. These results did not show evidence of a change in accuracy when participants experienced the unlearned sequence in block 11. If there really is no difference, then this would suggest that there was not a speed accuracy trade off for the disruption effect.

Participants were also asked if they thought the T ever followed a repeating sequence. Seventy percent of participants answered “yes.” Participant’s accuracy on the generation task (M = 25.69%; SD = 13.61%) was not significantly different from chance (25%), $t(22) = 0.24$, $p = .81$, 95% CI [19.81, 31.58], see Figure 8c. This finding indicates that although some participants reported being aware of a repeating pattern, participants in general were unable to produce the sequence themselves.

These results indicate that when the target is a popout and can be found quickly, then people can learn a repeating sequence of target locations in an environment with randomly moving distractors. This result counters the results of the 4th experiment in Toh et al. (2021) where they did not find evidence of sequence learning in an environment with a popout target and random distractors. This discrepancy between the results of these studies may be due to random chance. Their disruption effect in experiment 4A numerically had the correct pattern of results. Perhaps the effect size was small due to how they presented the sequence. The target

T's only appeared in the expected quadrants rather than in an exact sequence of locations as in the current study. Their variability in T location may have minimized participants' ability to learn the sequence. However, the current experiment used more complex SOC sequences which are harder to learn than the sequences Toh and colleagues used. But these two aspects are not necessarily equal in how they impact the ease in learning a sequence.

Experiment 3b, Random Distractors With A Non-Popout Target

Methods

Experimental 3b was the same as experiment 3a except that the target T was black, the same color as the distractor Ls.

Results and Discussion

Reaction time data was filtered to remove incorrect responses (11.28% of all trials) and trials with slow RT (1.75% of all trials). Slow trials were defined within each participant; trials were removed if they were slower than 3 SDs from that participant's average RT. These filters resulted in a total removal of 12.69% of trials (some trials fit multiple filters). These trials were not removed from accuracy data to fully assess proportion correct. Subjects were then removed from analysis if their RT or accuracy during the first 9 blocks was greater than 2 SDs from study average. Four participants were removed by this filter: Two participants were removed due to their RT being 2.45 SD and -2.22 SD from study mean RT and two participants were removed due to their accuracy being -3.82 SD and -2.46 SD from the study mean accuracy. Of the remaining 23 participants, sixteen participants identified as female, six identified as male, one identified as non-binary. Participants' ages ranged between 18 to 27 years old (M = 20.17 years old, SD = 2.21 years old).

In general, RT was within the range expected for visual search with a non-popout target (M = 1666.95 ms, SD = 390.89 ms). The learning effect was assessed over the course of the first 10 blocks, see Figure 8a. There was a significant negative correlation between RT and block, $r(228) = -.34$, $p < .001$, 95% CI [-.45, -.22]. A mixed regression model showed a significant negative relationship between RT and the log of block count (□ = -245.29 ms, SE = 35.92 ms, 95% CI [-316.11 ms, -174.46 ms], $t(206) = -6.83$, $p < .001$). These results indicate that participants had learned something during the first 10 blocks of the study and were able to respond faster. Accuracy was also assessed for possible speed accuracy trade off. Accuracy was quite high (M = 92.90%, SD = 5.60%). Similar to RT data, the change in accuracy was assessed over the course of the first 10 blocks. Accuracy and block were not significantly correlated, $r(228) = -.04$, $p = .50$, 95% CI [-.17, .09]. These results indicate that participants did not reliably increase or decrease their accuracy as the experiment went on and also that the RT learning effect was not due to a speed accuracy trade off.

The typical measure of sequence learning was assessed for each participant by taking their RT in block 11 and subtracting their average RT in block 10 and 12, see Figure 8b. The average RT increase (M = 89.71 ms; SD = 221.03 ms), was significantly different from zero, t(22) 1.95, p = .03, CI [10.57, Inf]). This finding suggests that people can learn a sequence of target locations when the target is a non-popout and the distractors are random.

The change in accuracy was also assessed for these last three blocks for an accuracy based disruption effect. Accuracy based disruption effect was assessed the same as the RT disruption effect. The average accuracy change (M = -3.93%; SD = 6.06%), was significantly different from zero t(22) -3.10, p = .005, CI [-6.55, -1.30]. This finding shows that there was a small but significant decrease in accuracy when participants experienced the unlearned sequence in block 11.

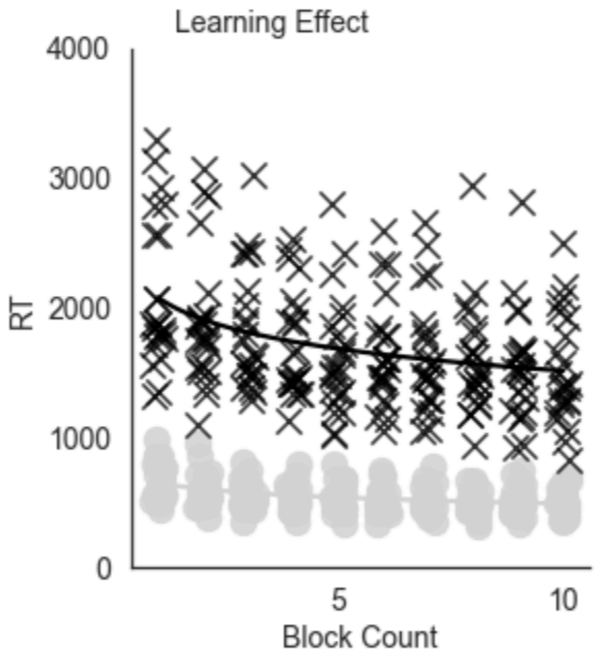
Participants were also asked if they thought the T ever followed a repeating sequence. Seventy four percent of participants answered “yes.” Participant’s accuracy on the generation task (M = 28.84%; SD = 15.18%) was not significantly different from chance (25%), t(22) = 1.22, p = .24, 95% CI [22.30%, 35.42%], see Figure 8c. This finding indicates that although some participants reported being aware of a repeating pattern, participants in general were unable to produce the sequence themselves.

These results indicate that when the target is a non-popout and the distractors change randomly, an environment that forces participants to visually search for the target on each trial, people can learn a repeating sequence of target locations. This result counters the results of the 5th experiment from Toh et al. (2021) where they had a white T among white Ls on a black background and did not find evidence for sequence learning. This inverse color (white on black rather than black on white) seems an unlikely explanation for our different findings. Toh and colleagues' study differed from the current study in the type of sequence used and the nature of the sequence. Perhaps these or random chance could explain the discrepancy. Regardless, the current study provides evidence that people can learn a sequence of target locations when they must always visually search for the target. This result suggests that the random eye movements required for non-popout search do not disrupt sequence learning.

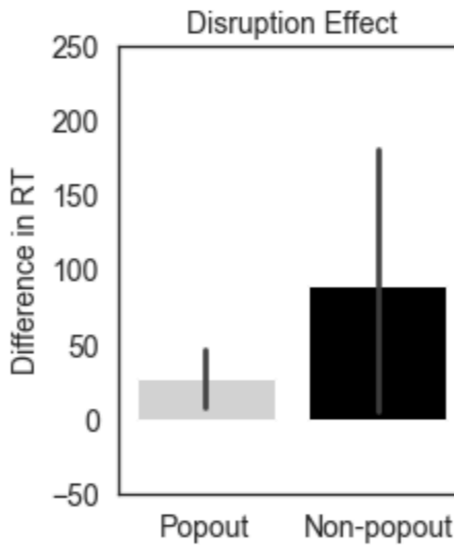
Figure 8

Performance With Random Distractors

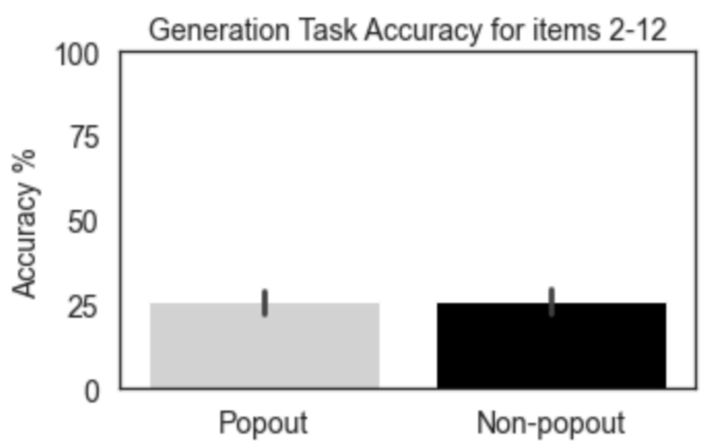
A



B



C



Note. (A) Learning effect, change in RT over the first 10 blocks of the Experiments 3a and 3b. Gray circles = popout target (Experiment 3a), black X = non-popout target (Experiment 3b). (B) Disruption effect, difference in RT between block 11 and the average of blocks 10 and 12. Error bars are 95% confidence intervals. (C) Generation task accuracy, with four possible responses, chance is 25%. Error bars are 95% confidence intervals.

Chapter 5: Across Experiment Comparisons

All of the above experiments were run concurrently and systematically varied the impact of target type (popout and non-popout) and distractor type (static, context, and random) therefore these experiments could be compared to explore the relative magnitude of the learning and disruption effects across these two factors. The planned sample size of 20 participants was to assess the individual experiments and this study likely does not have power to assess these cross experiment analysis. However, these analyses are included for completion and exploratory purposes.

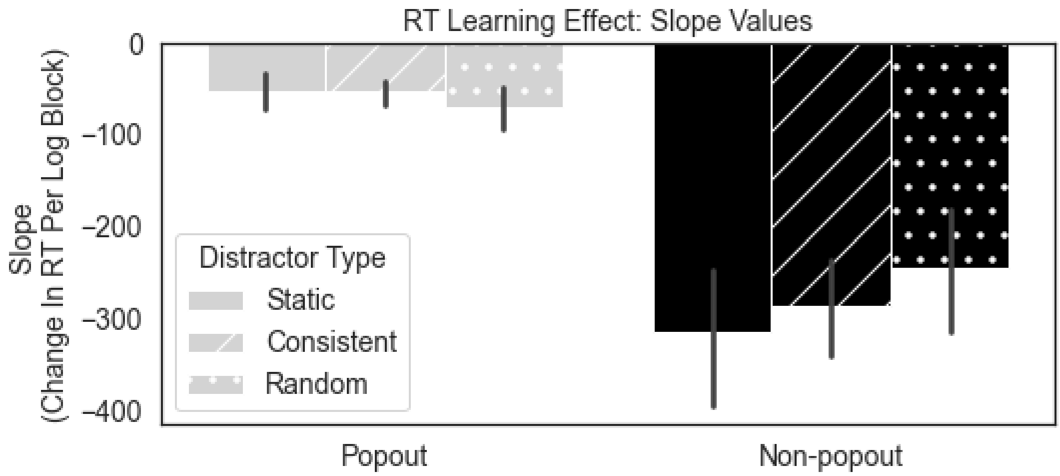
Learning Effect

The learning effect was first assessed by a correlation between block and RT over all conditions which showed a significant negative correlation between RT and block, $r(1338) = -.18$, $p < .001$, 95% CI [-.23, -.12]. The multiple regression model was significant and showed there was a significant interaction between log of block and target type with a steeper slope/greater learning effect for non-popout than popout targets, □ = -222.86 ms (SE = 20.99 ms, 95% CI [-264.03 ms, -181.69ms]), $t(1202) = -10.62$, $p < .001$. For a bar graph depiction of the slope values across all six experiments, see figure 9. For the distractor conditions, there was not an interaction between log of block and random distractors relative to static distractors, □ = 25.16 ms (SE = 25.71 ms, 95% CI [-25.28 ms, 75.60 ms]), $t(1202) = 0.98$, $p = .33$. Nor was there an interaction between log of block and consistent distractors relative to static distractors, □ = 12.14 ms (SE = 25.89 ms, 95% CI [-38.64 ms, 62.93 ms]), $t(1202) =$

0.47, $p = .64$. The model was re-coded to assess the interaction between log of block and consistent distractors relative to random distractors and this was also not significant, □ = -13.02 ms (SE = 25.44 ms, 95% CI [-62.93 ms, 36.89 ms]), $t(1202) = -0.51$, $p = .61$. Because the learning effect did not differ between the distractor conditions, the model was re-coded with the distractor types effects-coded to provide slope estimates averaged across these three distractor type conditions. For popout targets (Experiments 1a, 2a, and 3a) there was a -59.02 ms decrease in reaction time as log of block increased, □ = -59.02 ms (SE = 15.05 ms, 95% CI [-88.54 ms, -29.50 ms]), $t(1202) = -3.92$, $p < .001$. For non-popout targets (Experiments 1b, 2b, and 3b), there was a -281.88 ms decrease in reaction time as log of block increased, □ = -281.88 ms (SE = 14.61 ms, 95% CI [-310.55 ms, -253.22 ms]), $t(1202) = -19.29$, $p < .001$. Additionally, the model showed RT was slower at the start of the experiment for non-popout targets compared to popout targets, $t(130) = 23.93$, $p < .001$, but all distractor types were similar at experiment start, all $p > .05$. Slower RT with non-popout targets than popout is anticipated to occur if participants were indeed performing serial search when there was a non-popout target. The interaction showing a greater learning effect for non-popout compared to a popout targets is likely due to the greater benefit of learning in a serial (non-popout) search context. Thus, participants could have an equal amount of learning rather than greater learning because the same amount of learning could provide a greater time savings. The learning effect however did not differ between the search environments. This finding suggests that the distractor type has little impact on target location sequence learning.

Figure 9

Bar Graph Of Slope Values For The RT Learning Effect



Note. Slope values (Change in RT over the first 10 blocks of an experiment) presented as a bar graph The line graph forms are presented in each individual experiment. Error bars are 95% confidence intervals.

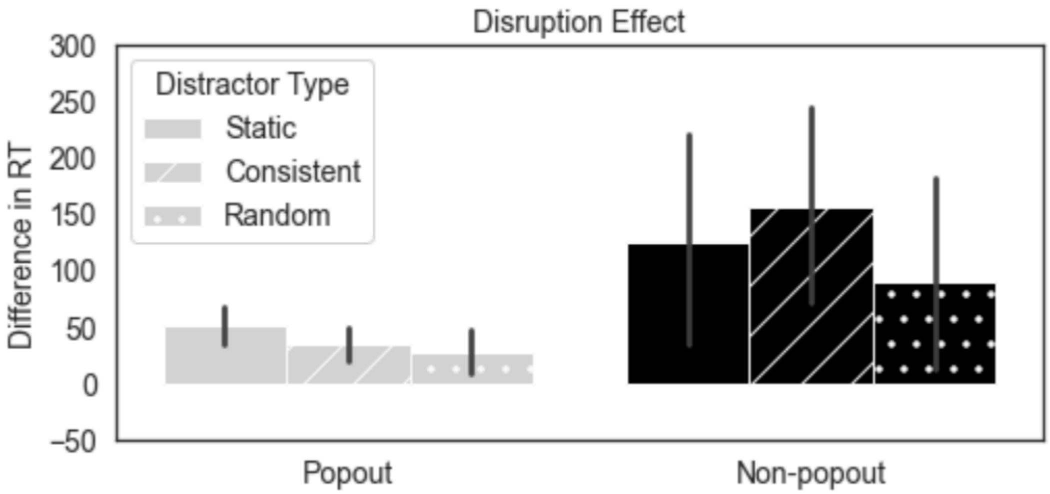
Disruption Effect

The disruption effect was assessed across experiments with a 2 X 3 ANOVA with two factors of target type (popout and non-popout) and three factors of distractor type (static, context, and random), see Figure10a. The interaction was not significant $F(2, 128)$ 0.42, p = .66, ges = .01. The disruption effect was not statistically different between static (M = 87.96 ms; SD = 156.29 ms), consistent (M = 102.77 ms; SD = 190.38 ms), and random (M = 58.87 ms; SD = 161.14 ms), $F(1, 128)$ 0.63, p = .53, ges = .01. There was a main effect of target popout, $F(1, 128)$ 8.94, p = .003, ges = .07. A Welch's t-test showed the disruption effect was larger with a non-popout target (M = 125.09 ms; SD = 225.91 ms) than with a popout target (M = 38.21ms; SD = 41.74 ms), t(73) -3.14, p = .002, CI [-142.05, -31.69]. However, these two effects may have differed due to a difference in base RT, see Figure10b. In environments such as when there is a non-popout target or when there are changing distractors, people may be slower to find the target in general. The disruption in RT would be larger in more difficult environments because knowing where to find a target provides greater time savings in difficult environments than easy environments. Therefore, the above analysis was also conducted with percent change in RT (the disruption effect was divided by the average of block 10 and 12 and this was multiplied by 100). The percent change values were entered into the 2 X 3 ANOVA and, again, the interaction was not significant $F(2, 128)$ 0.28, $p = .76$, ges = .004. Also, the disruption effect was not significantly different between static (M = 11.52%; SD = 14.33%), consistent (M = 10.40%; SD = 13.58%), and random (M = 7.17%; SD = 17.30%) $F(1, 128)$ 0.95, $p = .39$, ges = .02. At least numerically, there was a gradation of learning effects in the popout conditions with static distractors leading to the greatest disruption and decreasing with increasing distractor variability. However, a one-way ANOVA comparing the three popout conditions alone was not significant, $F(2, 62)$ 1.98, $p = .15$, ges = .06. The main effect of target type was no longer statistically significant, $F(1, 128)$ 0.67, $p = .41$, ges = .01. This was further found by a Welch's t-test that showed the difference between non-popout target (M = 10.74%; SD = 19.46%) and popout target (M = 8.50%; SD = 8.62%) disruption effects, t(95) -0.87, p = .39, CI [-2.87%, 7.35%] was not significantly different. This analysis is not conclusive but shows that when percent change in RT is used there is no longer evidence that a non-popout target leads to a greater disruption effect.

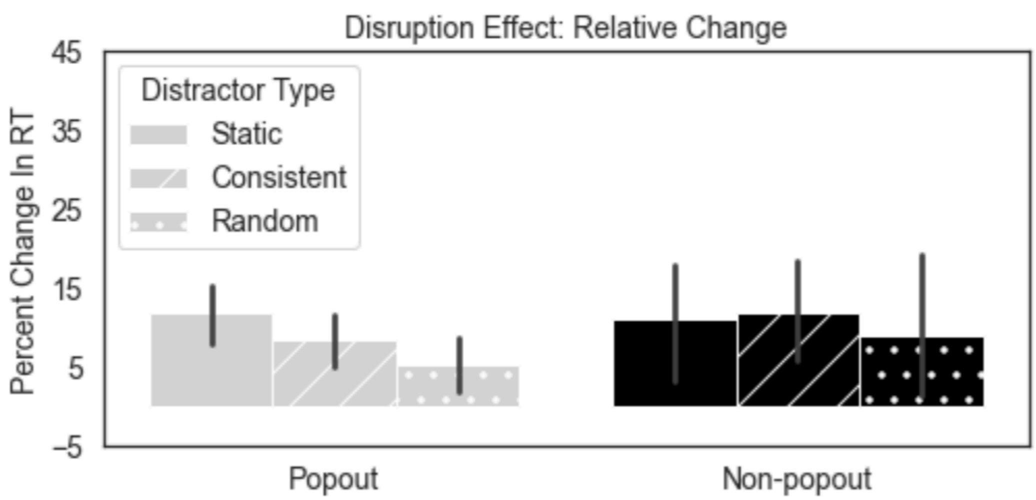
Figure 10

Disruption Effect And Relative Disruption Effect Across All Six Experiments

A



B



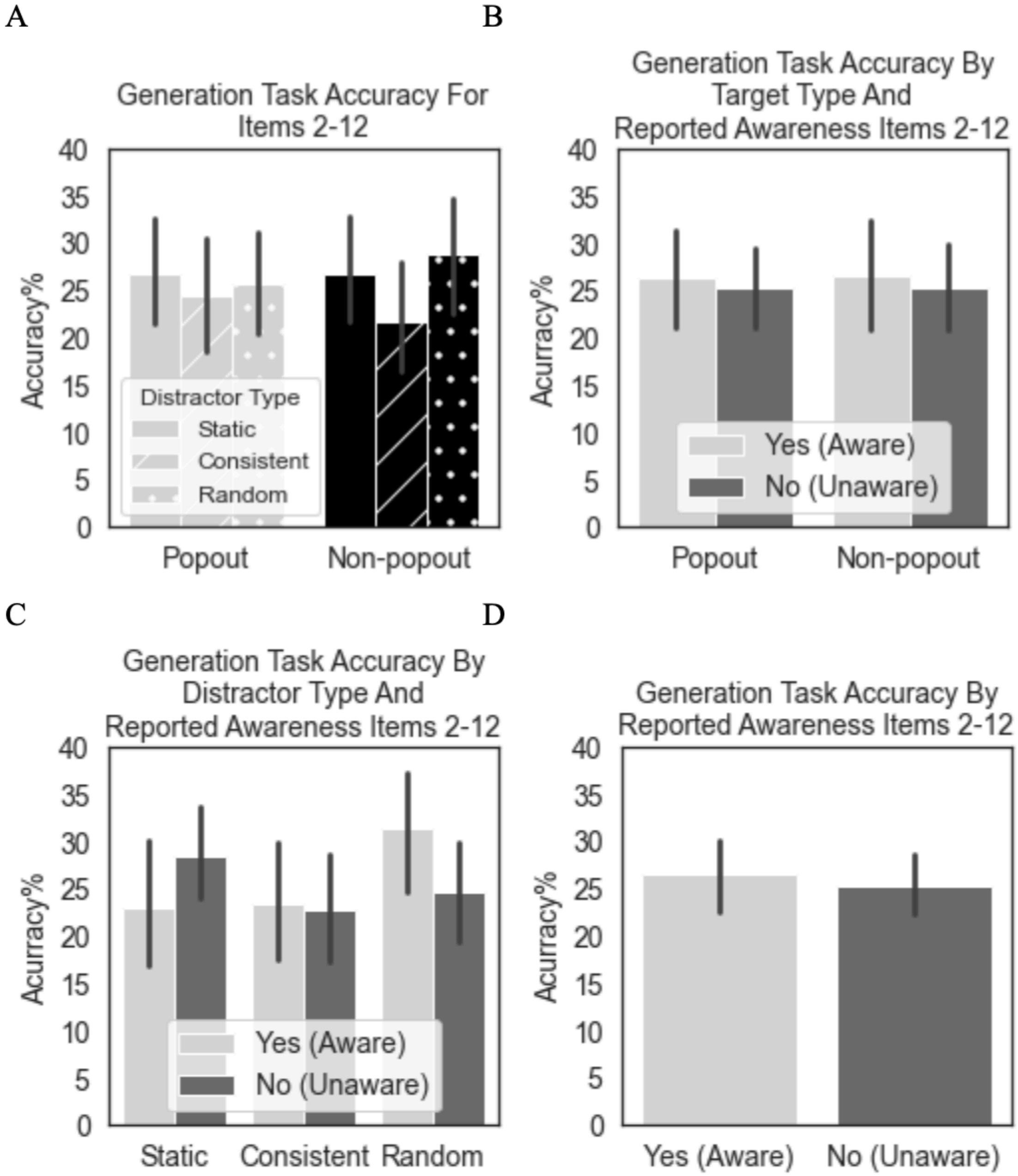
Note. (A) Disruption effect across all 6 conditions. (B) Disruption effect plotted as percent change (the disruption effect was divided by the average of block 10 and 12 and multiplied by 100). Error bars are 95% confidence intervals.

Explicit Awareness And Generation Task Performance

Another possible explanation for why there are not detectable differences between the distractor types could be related to explicit awareness of the sequence. When people are explicitly aware, they could exert conscious effort to learn to sequence. This could minimize differences in conditions by showing an effect when one might not otherwise be present or would otherwise be smaller. Across all six experiments more than 50% of participants reported being explicitly aware of some kind of a target location pattern, but participants' performance on the generation tasks in each experiment was at chance, see Figure11a. Each individual experiment was unable to assess if performance on the generation task was different for participants who reported being aware compared to unaware because some conditions had very few participants who reported being unaware. In this cross experiment analysis, generation task performance was assessed for participants who reported being aware and unaware across all experiments. Whether performance was collapsed across to assess target type or distractor type (see figure 11b and 11c) all confidence intervals included 25% indicating that their performance was not significantly different from chance. The tests used were one sample t-tests and, when distributions were non-normal as indicated by Shapiro-Wilk tests, one-sample Wilcoxon Signed Rank Tests, all $p > .05$. When all reported aware participants were compared to reported unaware on generation task accuracy, a Shapiro-Wilk test showed both were non-normal, $p < .05$, and one-sample Wilcoxon Signed Rank Tests were used. Participants who reported being aware of a target pattern had generation task performance that was not significantly different from 25%, $V = 1884$, $p = .63$, 95% CI [22.73%, 27.27%] and those who reported being unaware were also not significantly different from 25%, $V = 565$, $p = .59$, 95% CI [22.73%, 31.82%], see figure 11d.

Figure 11

Generation Task Accuracy, Chance Is 25%



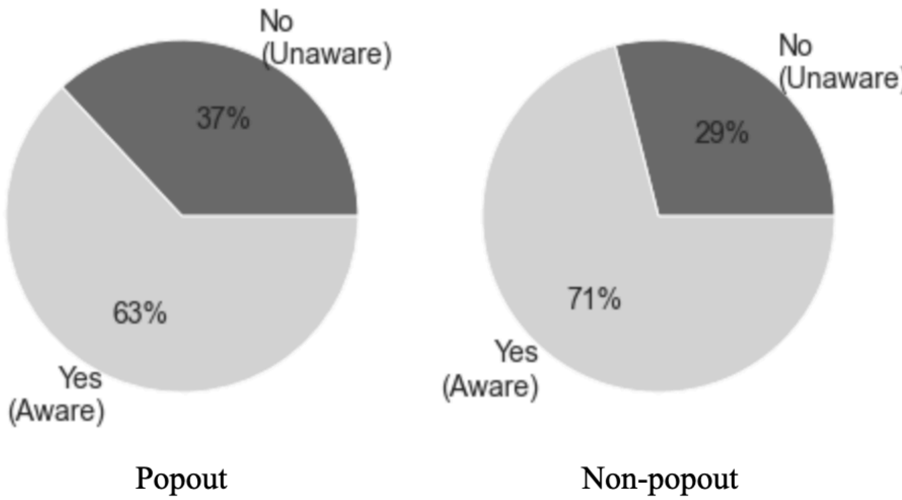
Note. (A) Generation task performance across all experiments. (B) Generation task performance by target type and reported awareness (C) Generation task performance by distractor type and reported awareness (D) Generation task performance by reported awareness only. Error bars are 95% confidence intervals.

Generation task accuracy may be low because people are unlikely to learn the entire 12 item sequence, they might only learn the beginning, or some subset. Later performance may also be poorer because participants lose track of their place with each trial. In the generation task, participants only performed one 12 item sequence for the generation task, therefore this data will be analyzed by a chi-square test on the proportion of participants who answered correctly relative to the number expected by chance (25% of total participants, rounded to the nearest whole number). For trial 2, their first guess trial, the proportion of correct participants (38.81% of participants) was significantly greater than chance $X^2(1, N = 268) = 4.95$, $p = .03$. However, all subsequent trials were not significantly different from change, all $p > .05$. Percentages of proportion correct participants are as follows: trial three 31.34%, trial four 26.12%, trial five 20.15%, trial six 23.88% trial seven 24.63%, trial eight 20.15%, trial nine 20.90%, trial ten 26.12%, trial eleven 23.88%, trial twelve 26.87%. This finding suggests that despite high rates of reported awareness participants were unable to generate the sequence themselves even at the start of the sequence.

Additionally, past research suggested that a longer interval might increase the likelihood of participants developing explicit awareness (Destrebecqz & Cleeremans 2003). However, there was not a difference in the ratio of participants who reported being aware/unaware between popout and non-popout conditions, $X^2(1, N = 134) = 0.63$, $p = .43$, see Figure 12. These results are inconclusive but, if there really is no difference between these two, then this result suggests longer intervals, filled with visual search, do not increase explicit awareness.

Figure 12

Proportion of Participants Who Reported Being Aware and Unaware

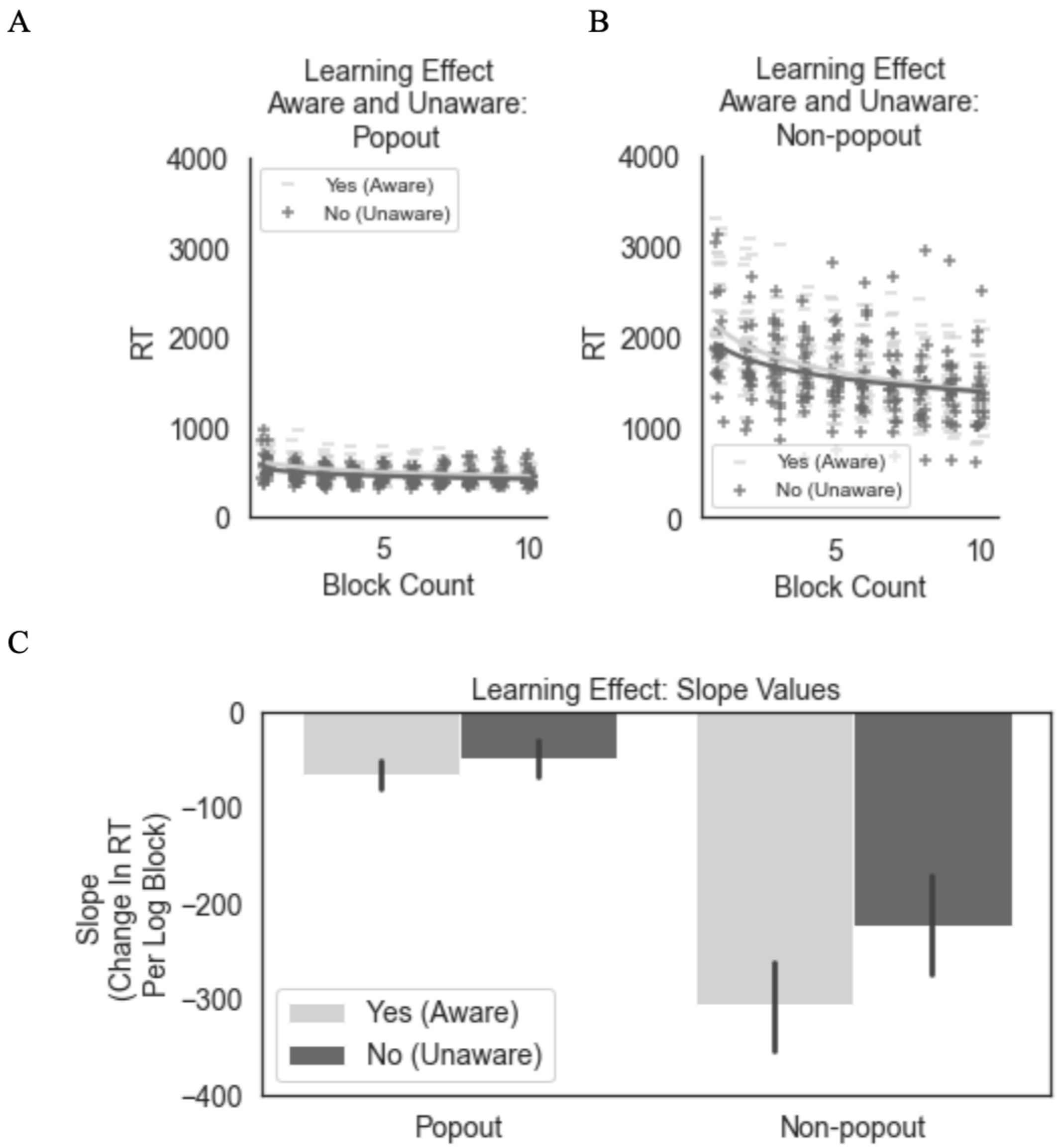


Note. Proportion of participants reported being aware or unaware in the popout and non-popout conditions.

Performance on the generation task might not truly reflect explicit awareness if the change in task, with the target no longer being present, interfered with the expression of learning. Therefore, the learning effect (and later also the disruption effect) was compared between aware and unaware participants, see Figure 13. The multiple regression model added reported awareness as a predictor with unaware as the reference condition and distractor type was removed as a predictor. The model was significant and again showed a significant interaction between log of block and target type with a steeper slope/greater learning effect for non-popout than popout targets, □ = -218.85 ms (SE = 20.64 ms, 95% CI [-259.35 ms, -178.36ms]), t(1202) = -10.60, p < .001. There was also an interaction between log of block and aware compared to unaware with there being a steeper slope/greater learning effect for participants who reported being aware than unaware, □ = -48.63 ms (SE = 21.96 ms, 95% CI [-91.72 ms, -5.54 ms]), t(1202) = -2.21, p = .03. The different slope values for all conditions are as follows: popout targets and aware participants, □ = -76.77 ms (SE = 16.84 ms, 95% CI [-109.81 ms, -43.73 ms]), t(1202) = -4.56, p < .001. Popout targets and unaware participants, □ = -28.14 ms (SE = 20.24 ms, 95% CI [-67.85 ms, 11.57 ms]), t(1202) = -1.39, p = .16. Non-popout targets and aware participants, □ = -295.62 ms (SE = 15.67 ms, 95% CI [-326.38 ms, -264.87 ms]), t(1202) = -18.86, p < .001. Non-popout targets and unaware participants, □ = -246.99 ms (SE = 21.18 ms, 95% CI [-288.54 ms, -205.45 ms]), t(1202) = -11.66, p < .001. Not finding a learning effect for participants who reported being aware and had popout targets is likely due to a floor effect. At the start of the experiment these participants' RT was 497.82 ms. The greater learning effect for participants who reported being aware compared to unaware could suggest greater amounts of sequence learning but the learning effect is made up of many possible aspects that participants could be learning.

Figure 13

Learning Effect Across All Six Experiments Separated by Target Type

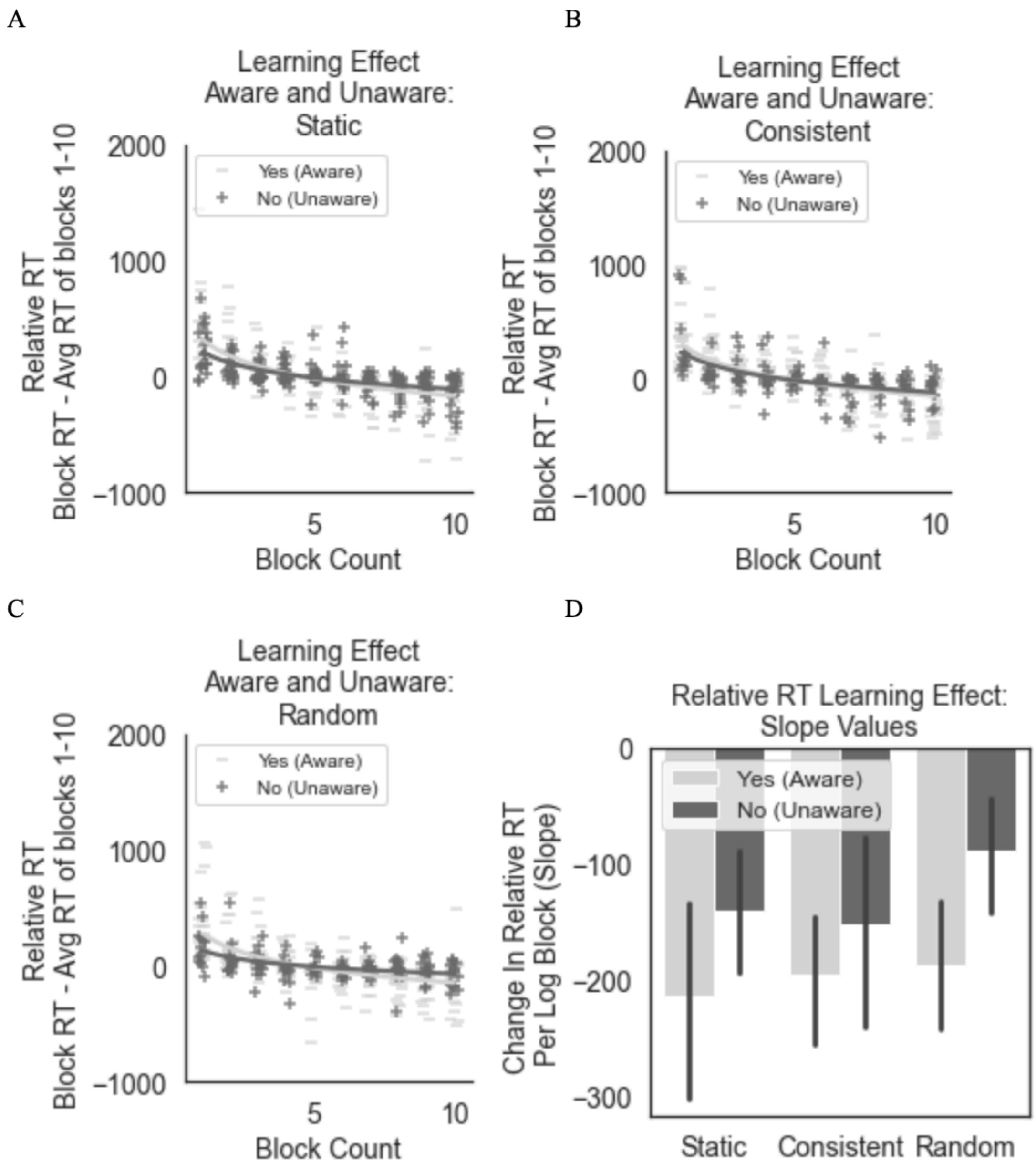


Note. (A) Learning effect separated by participants who reported being aware and unaware with popout target conditions. Curves are exponential. (B) Learning effect separated by participants who reported being aware and unaware with non-popout target conditions. Curves are exponential. (C) Slope values plotted as a bar graph, error bars are 95% confidence intervals.

The learning effect between reported aware and unaware participants was also assessed for the distractor types but due to the large baseline difference in RT between popout and non-popout targets, these groups cannot be collapsed across without some kind of adjustment. Adjusting the RT as percent difference from average RT removes too much variability to support a multiple regression and, unlike the disruption effect, the main interest is not to assess percent change but instead to remove baseline differences in RT. Therefore, relative RT will be defined as a participant's RT in a block minus their average RT over all the 10 learning effect blocks, see Figure 14. These relative RTs were entered into the multiple regression model and, like the above analysis, added reported awareness as a predictor with unaware as the reference condition and removed target type as a predictor. Participants were included with random intercepts (there was not sufficient variation in participant slopes to support a random participant slopes model). The model was significant and again showed an interaction between log of block and aware participants compared to unaware with there being a steeper slope/greater learning effect for participants who reported being aware compared to unaware, □ = -71.64 ms (SE = 13.17, 95% CI [-97.47 ms, -45.81 ms]), $t(1202) = -5.44$, $p < .001$. For the distractor types, the interaction between log of block and consistent distractors, relative to static distractors was not significant, □ = 9.72 ms (SE = 15.22, 95% CI [-20.15 ms, 39.59]), $t(1202) = 0.64$, $p = .52$. The interaction between log of block and consistent distractors, relative to random distractors was also not significant, □ = -24.26 (SE = 14.80, 95% CI [-53.29 ms, 4.77 ms]), $t(1202) = -1.64$, $p = .10$. There was a significant interaction between log of block and random distractors, relative to static distractors with there being a steeper slope/greater learning effect for static distractors than random distractors, □ = 33.98 ms (SE = 15.12, 95% CI [4.32 ms, 63.63 ms]), $t(1202) = 2.25$, $p = .02$. The different slope values for all conditions are as follows: aware and static distractors, □ = -211.95 (SE = 12.23, 95% CI [-235.95 ms, -187.95 ms]), $t(1202) = -17.33$, $p < .001$, aware and consistent distractors, □ = -202.23 ms (SE = 11.09 ms, 95% CI [-223.99 ms, 180.47 ms]), $t(1202) = -18.23$, $p < .001$, aware and random distractors, □ = -177.97 ms (SE = 11.05 ms, 95% CI [-199.65 ms, -156.29 ms]), $t(1202) = -16.11$, $p < .001$, unaware and static distractors, □ = -140.31 ms (SE = 13.03, 95% CI [-165.88 ms, -114.74 ms]), $t(1202) = -10.77$, $p < .001$, unaware and consistent distractors, □ = -130.59 ms (SE = 14.28 ms, 95% CI [-158.61 ms, -102.58 ms]), $t(1202) = -9.15$, $p < .001$, unaware and random distractors, □ = -106.33 (SE = 14.05, 95% CI [-133.90 ms, 78.76 ms]), $t(1202) = -7.57$, $p < .001$. These results showed greater learning effect for participants who reported being aware compared to unaware and greater learning effect for static distractors compared to random distractors. Greater learning effects suggest greater sequence learning however, a caveat is awareness was self-reported and what patterns participants were aware of is unclear. Also, the greater effect may be related to some other aspect such as conscientiousness leading them to be more likely to notice and report being aware of any kind of target location pattern and make them more likely to get better at the task over time unrelated to sequence learning. If this effect is due to different amounts of sequence learning then it suggests that perhaps participants could learn the sequence better if they were aware that the target followed a pattern, even if they could not generate that sequence themselves. Furthermore, the learning effect was also greater for static distractors compared to random distractors suggesting there was less sequence learning or it was harder to achieve learning with random distractors compared to static distractors. Note, this difference in this model may be an artifact of this analysis in trying to collapse data (target type) that really should not be collapsed across and this finding should be taken with a grain of salt.

Figure 14

Learning Effect Across All Six Experiments Separated by Distractor Type



Note. Due to large differences in RT between popout and non-popout conditions, RT in each block was equated by subtracting the average RT for the 10 blocks for that condition. Curves are exponential with 95% confidence intervals. (A) Learning effect separated by participants who reported being aware and unaware with static distractor conditions. (B) Learning effect separated by participants who reported being aware and unaware with consistent distractor conditions. (C) Learning effect separated by participants who reported being aware and unaware with random distractor conditions. (D) Slope values plotted as a bar graph, error bars are 95% confidence intervals.

The impact of reported explicit awareness on the disruption effect was also assessed. This analysis was first collapsed across the distractor types and used a 2 X 2 ANOVA with two factors of reported awareness and two factors of target popout, see Figure 15. The interaction was not significant $F(1, 130)$ 3.15, $p = .08$, ges = .02. This result was also found when using percent change in RT, $F(2, 130)$ 3.89, $p = .051$, ges = .03. Participants' reported awareness was also directly compared with Welch's t-test within each target type, Bonferroni corrected. For the popout conditions, the disruption effect for aware (M = 33.21 ms; SD = 42.11 ms) compared to unaware (M = 46.75 ms; SD = 40.53 ms) participants was not significantly different, t(50) -1.28, p = .21, CI [-37.96 ms, 10.90 ms]. For the non-popout conditions, the disruption effect for aware (M = 152.12 ms; SD = 230.56 ms) compared to unaware (M = 58.84 ms; SD = 204.58 ms) was also not significantly different, t(40) , p = .11, CI [-38.05 ms, 224.62 ms]. These comparisons were also not significant when using relative change: popout aware (M = 7.36%; SD = 8.78%) vs unaware (M = 10.44%; SD = 8.15%), t(51) -1.43, p = .16, CI [-8.06%, 1.89%] and non-popout aware (M = 13.02%; SD = 20.23%) vs unaware (M = 5.14%; SD = 16.60%), t(43) 1.68, p = .10, CI [-3.04%, 18.81%]. If there really is no difference, this finding indicates that awareness of some kind of target location pattern did not impact the disruption effect among the different target types and suggests that awareness does not influence sequence learning.

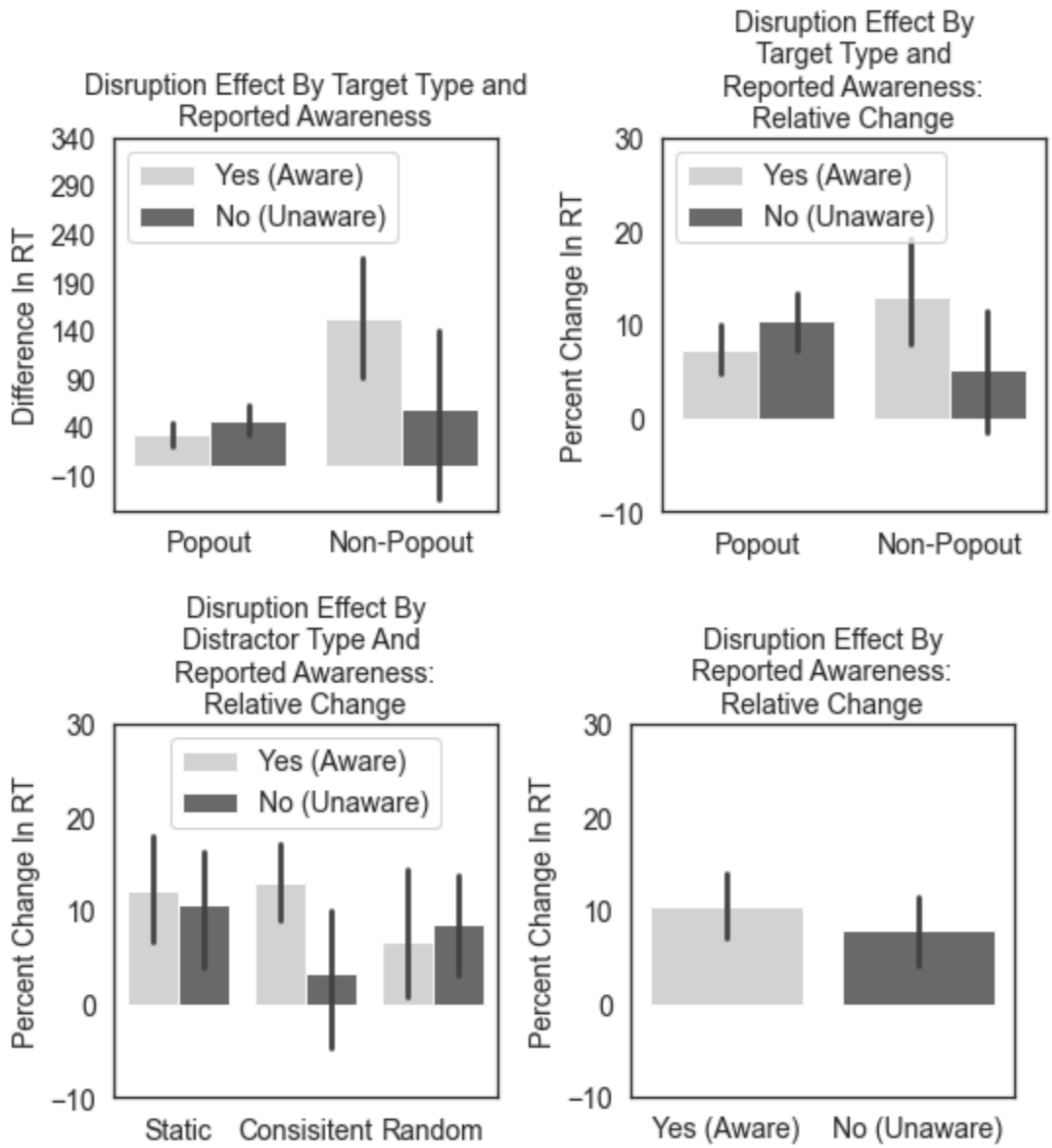
Additionally, the disruption effect was assessed with a 2 X 3 ANOVA with two factors of reported awareness and three factors of distractor type, see Figure 14. This analysis used percent change only because this analysis collapses across the target type conditions which have large baseline RT differences that can result in greater disruption effects for non-popout conditions. The interaction between reported awareness and distractor type was not significant, $F(2, 128)$ 1.36, $p = .26$, ges = .02. Participants' reported awareness was also directly compared with Welch's t-test within each distractor type, Bonferroni corrected. For static distractor conditions, the disruption effect for aware (M = 12.23%; SD = 15.10%) compared to unaware (M = 10.62%; SD = 13.66%) participants was not significantly different, t(40) 0.36, p = .72, CI [-9.34%, 12.55%]. For consistent distractor conditions, the disruption effect for aware (M = 12.95%; SD = 12.85%) compared to unaware (M = 3.38%; SD = 13.57%) participants was not significantly different, t(19) 2.12, p = .05, CI [-2.25%, 21.39%]. For random distractor conditions, the disruption effect for aware (M = 6.34%; SD = 19.48%) compared to unaware (M = 8.53%; SD = 10.38%) participants was not significantly different, t(39.73) -0.43, p = .67, CI [-12.98%, 9.19%]. If there really is no difference, this finding indicates that awareness of some kind of target location pattern did not impact the disruption effect among the different distractor types and suggests that awareness does not influence sequence learning. These analyses show no evidence for awareness impacting the disruption effect among the target and distractor conditions. All conditions were collapsed and compared with percent change. A Shapiro-Wilk test indicated that the participants who reported being aware were significantly different from normal, p < .001. Thus, a Mann-Whitney U test was used and showed that participants who reported being aware and unaware were not significantly different W = 1935, p < .83, 95% CI

[-5.42%, 4.07%]. Although these tests are inconclusive on whether there is or is not a difference between these two groups of participants, the critical question is if participants who report being unaware show a disruption effect significantly different from zero. A one-sample Wilcoxon Signed Rank Tests were used and showed that both participants who reported being aware, $V = 3242$, $p < .001$, 95% CI [6.36%, Inf] and those who reported being unaware, $V = 810$, $p < .001$, 95% CI [5.13%, Inf] had non-zero disruption effects indicating that awareness is not required to have a disruption effect. This finding aligns with the finding that explicit awareness is not required for sequence learning from studies with low rates of awareness (Toh et al. 2021) and studies that show evidence of sequence learning when explicitly aware participants are removed (Goschke & Bolte, 2012). The conditions that were or were not significantly different from zero for the disruption effect are presented in Table 2. Some of these subgroups did not have the recommended sample size of 20 participants so some conditions lack statistical power.

Figure 15

Disruption Effect Across All Six Experiments

A B



C D

Note. Disruption effect separated by participants who reported being aware and unaware. (A) Shows popout vs non-popout. (B) Shows popout vs non-popout as percent change in RT. (C) Shows Static vs Consistant vs random distractors as percent change in RT. (D) Shows all participants who reported being aware and unaware as percent change in RT. All error bars are 95% confidence intervals.

Table 2
Summary of disruption effect and reported awareness results

Collapsed by distractor type (popout conditions)						
Condition	Type of analysis	Number of participants	Statistic	p-value	95% CI	* = sig. - = not sig.
Popout target and aware	RT difference	41	t = 5.05	>.001	[22.15 ms, Inf]	*
	Percent change	41	t = 5.37	>.001	[5.05%, Inf]	*
Popout target and unaware	RT difference	24	t = 5.65	>.001	[32.57 ms, Inf]	*
	Percent change	24	t = 6.28	>.001	[7.59%, Inf]	*
Non-popout target and aware	RT difference	49	t = 4.62	>.001	[96.88 ms, Inf]	*
	Percent change	49	V = 1015	>.001	[6.97%, Inf]	*
Non-popout target and unaware	RT difference	20	t = 1.29	.11	[-20.26 ms, Inf]	-
	Percent change	20	t = 1.38	.09	[-1.28%, Inf]	-
Collapsed by target popout (distractor conditions)						
Condition		Number of participants	Statistic	p-value	95% CI	
Static distractors and aware	RT difference	24	V = 252	.001	[32.12 ms, Inf]	*
	Percent change	24	t = 3.97	< .001	[6.95%, Inf]	*

Static distractors and unaware	RT difference	19	V = 155	.007	[21.57 ms, Inf]	*
	Percent change	19	t = 3.39	.002	[5.19%, Inf]	*
Consistent distractors and aware	RT difference	33	V = 502	<.001	[59.16 ms, Inf]	*
	Percent change	33	t = 5.79	<.001	[9.16%, Inf]	*
Consistent distractors and unaware	RT difference	12	V = 51	.19	[-71.11 ms, Inf]	-
	Percent change	12	t = 0.86	.20	[-3.65%, Inf]	-
Random distractors and aware	RT difference	33	V = 357	.09	[-5.39 ms, Inf]	-
	Percent change	33	V = 389	.03	[0.72%, Inf]	*
Random distractors and unaware	RT difference	13	V = 77	.01	[18.28 ms, Inf]	*
	Percent change	13	t = 2.96	.006	[3.40%, Inf]	*

Note. Disruption effect analysis comparing participants who reported being aware and unaware separated by target type and distractor type.

Additionally, all the analyses so far have focused on the magnitude of the disruption effect. However, further insights could be found from the proportion of people who showed a positive disruption effect. Significant disruption effects reported earlier could have been driven by a few participants with very large magnitude effects. Also, the greater the proportion, the more likely it is that any one person would show an effect, and suggests that the effect is more pervasive. For a majority of the conditions, there were far more participants showing a positive vs zero or negative effect, see Table 3. However, for the non-popout random condition there was a similar number of participants who did (13) and did not (10) show a disruption effect. This proportion though was not significantly different from the other random condition, popout random, $X^2(1, N = 46) = 1.58$, $p = .21$, nor from the other non-popout conditions, non-popout static $X^2(1, N = 44) = 0.003$, $p = .96$ or non-popout consistent, $X^2(1, N = 48) = 0.67$, $p = .41$. Numerically, fewer participants in this (non-popout random) condition showed a positive disruption effect than other corresponding conditions but this difference was not significant. If there truly is no difference, then someone in this condition is just as likely to show a disruption effect as someone in another condition and many conditions in general show people are likely to have a positive disruption effect.

Table 3

Proportion of Participants Who Had a Positive Disruption Effect

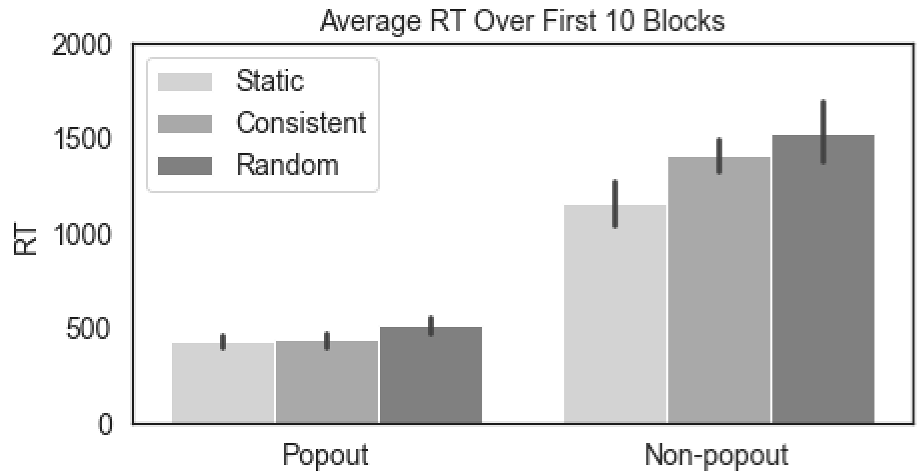
Condition	Proportion of Positive vs negative or zero disruption effect
Popout target, Static Distractors	20 vs 2
Non-popout target, Static Distractors	13 vs 8
Popout target, Consistent Distractors	18 vs 2
Non-popout target, Consistent Distractors	18 vs 7

Popout target, Random Distractors	18 vs 5
Non-popout target, Random Distractors	13 vs 10

Note. Proportions of participants who had a positive disruption effect.

One assumption of this dissertation was that different distractor environments would produce different amounts of visual search. Although this dissertation did not collect eye tracking data, this issue can be somewhat approximated by differences in visual search time. To assess differences in baseline RT between conditions, RTs across the first 10 blocks were average for each condition and imputed into a 2 X 3 ANOVA with two factors of target type (popout and non-popout) and three factors of distractor type (static, context, and random), see Figure 16. The interaction was significant $F(2, 128)$ 4.68, $p = .01$, ges = .07. The difference between popout and non-popout targets is to be expected, therefore the pairwise analysis will be among the distractor conditions. A Shapiro-Wilk test indicated that several of the condition's distributions differed significantly from normal, $p > .05$ therefore Mann-Whitney U tests were used. For the popout conditions, static distractors (M = 431.94 ms; SD = 72.01 ms) were not significantly different from consistent distractors, (M = 441.04 ms; SD = 83.16 ms), $W = 202$, $p = .66$, 95% CI [-59.46 ms, 48.30 ms]. However, static distractors were significantly different from random distractors (M = 518.31 ms; SD = 97.16 ms), $W = 125$, $p = .003$, 95% CI [-153.56 ms, -27.51 ms]. Also, consistent distractors were significantly different from random distractors, $W = 107$, $p = .002$, 95% CI [-151.41 ms, -18.91 ms]. For the non-popout conditions, static distractors (M = 1155.29 ms; SD = 289.47 ms) were significantly different from consistent distractors, (M = 1412.26 ms; SD = 222.34 ms), $W = 121$, $p = .001$, 95% CI [-446.67 ms, -88.27 ms]. Static distractors were also significantly different from random distractors (M = 1528.11 ms; SD = 422.63 ms), $W = 115$, $p = .002$, 95% CI [-615.97 ms, -93.21 ms]. However, consistent distractors were not significantly different from random distractors, $W = 255$, $p = .51$, 95% CI [-326.11 ms, 159.50 ms]. These findings suggest that the popout target minimized differences between the static and consistent distractor conditions but did not prevent random distractors from perhaps increasing visual search demands. These results also suggest that in the non-popout conditions, the dynamically changing distractors may have increased the visual search demands compared to the static distractors. The pattern of results is inline with the assumptions of this dissertation that a non-popout target requires more visual search time than a popout target. However, not all distractor type conditions were significantly different. In particular, non-popout consistent and non-popout random conditions did not differ. Contextual cueing was expected to minimize visual search demands and there was evidence of this with popout targets but not with non-popout. Because all conditions showed evidence of sequence learning, though, minimizing visual search seems to be a non-issue.

Figure 16
Baseline Differences In Visual Search Time

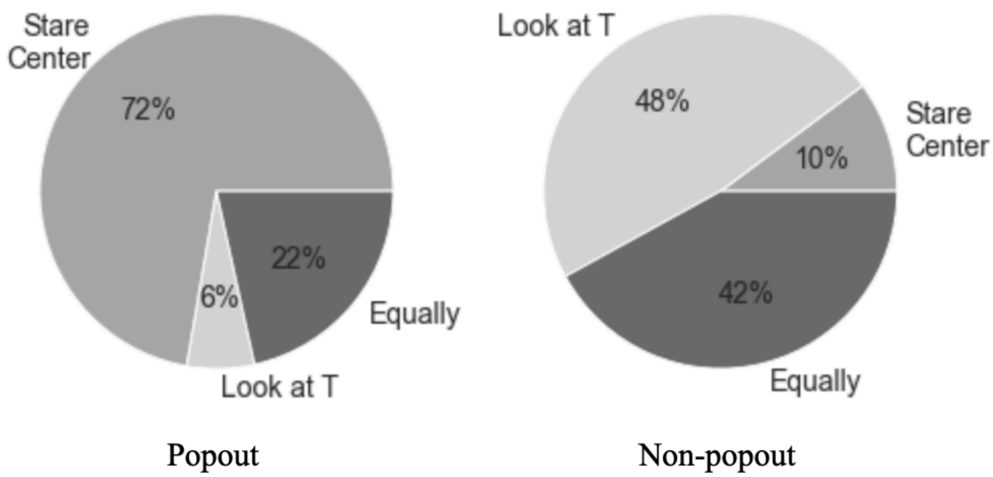


Note. RT averaged over the first 10 blocks to assess differences in baseline RT. Error bars are 95% confidence intervals.

Another assumption of this dissertation was that people would be engaging in visual search in typical visual search tasks. Although this dissertation did not use an eye tracker, it began to explore this idea by asking participants what visual search strategies they used. Participants were asked "which strategy did you use the majority of the time?" (Stare at the center of the screen and find the T with peripheral vision, Look at the T, or Did both about equally). The results can be seen in Figure 17. A majority of participants in the popout target conditions stated a the center of the screen and used peripheral vision, whereas, a majority of participants in the non-popout conditions looked for the target. This confirms visual search literature that people need to search for a target in environments that have a non-popout target. However, not all participants used this strategy; many participants sometimes used their peripheral vision. The ~10% of participants who reported using peripheral vision is too small to assess impacts on learning effects and disruption effects, however, and many participants also reported using a mix of both strategies. These results further suggest that future research should incorporate an eye tracker to assess how eye movements impact sequence learning.

Figure 17

Proportion Of Reported Eye Movement Strategies



Note. (A) Eye movement strategy reported for popout target conditions. (B) Eye movement strategy reported for non-popout target conditions.

Chapter 6: General Discussion

This dissertation addresses a gulf in understanding between two major areas of study. There is a vast literature on visual search and a vast literature on sequence learning, but despite these rich areas, few studies explore sequence learning in sequential visual search. Sequential visual search is also a pervasive everyday experience e.g. searching through a series of user interfaces, and this research could have implications for technology design and redesign. In particular, understanding which environments lead people to learn and rely on their visual search habits could reveal which environments that, when updated and no longer follow those expectations, would result in performance disruptions and potentially painful frustration. This dissertation investigated the impact of visual search demands (i.e. popout vs non-popout targets) and distractor environment (i.e. static vs consistently changing contexts vs random distractors) on the development of sequence learning. Literature on sequence learning with the SRT task suggests the ability to learn a sequence of visual search target locations may depend on visual search demands. However, previous research assessed sequence learning in environments with minimal search demands such as use of a popout target (Toh et al. 2021) or one target with three distractors presented in a horizontal line, a design very dissimilar to typical visual search studies (Deroost et al., 2009). To address this issue, this dissertation assesses sequence learning with non-popout targets in a traditional T among Ls visual search task. If visual search disrupts sequence learning, then sequence learning may also depend on the type of distractor environment. Research on visual search indicates that a learnable search environment can help reduce the need for visual search. In particular, contextual cueing is a phenomenon where people learn several search environments and can more quickly and efficiently find a target in familiar vs unfamiliar search environments. Whether a search context could enable (or enhance) sequence learning by being an additional environmental cue was unknown and this dissertation investigated this question as well.

Which Environments Support Sequence Learning?

This dissertation found evidence of sequence learning for all combinations of target type (popout and non-popout) and distractor type (static, context, random). All conditions showed a significant learning effect; participants were faster with each additional block. This effect could be due to learning the sequence, learning how to search within the distractors, and/or general task learning. Critically, all conditions showed a significant disruption effect, the canonical measure of sequence learning; participants' RT was significantly slower when the sequence did not follow the learned sequence compared to when it followed the learned sequence immediately preceding and postceding that disruption. These findings suggest that people learned the sequence, and came to rely on that knowledge in a variety of search environments. These findings indicate that sequence learning is surprisingly robust in visual search which is directly counter to the conclusions of Toh et al. (2021) and counter to predictions suggested by SRT literature that visual search should disrupt sequence learning. For a comparison between the results Toh et al. (2021) and this dissertation, see Table 4.

Table 4

Results comparison to Toh et al. (2021)

Popout vs non popout	Distractor Type	Toh et al. (2021) Sequence learning	Current Dissertation Sequence learning
Popout	Static	Yes	Yes
Non-popout	Static	–	Yes

Popout	Consistent Contexts	–	Yes
Non-popout	Consistent Contexts	–	Yes
Popout	Random	No	Yes
Nonpopout	Random	No	Yes

Note. Comparison between Toh et al. (2021) and the current dissertation. Dash (–) indicate experiments that were not tested in Toh et al. (2021).

One key extension of this dissertation compared to Toh et al. (2021) was that this dissertation used SOC sequences. This type of sequence was used to equate transition probabilities between the learned sequence and the disruption sequence (Reed & Johnson, 1994). Toh et al. (2021) did not control for this issue and differences in transition probabilities could have explained the disruption effects seen in their experiments (Reed & Johnson, 1994). Additionally, using SOC sequences ensures that participants are learning sequences of at least three elements or more because, to know the next item in the sequence, you need to know the previous two items. Furthermore, SOC sequences are more complicated than transition probabilities and would be more difficult to learn and this dissertation found that people can learn SOC sequences in visual search environments.

Another major difference between Toh et al. (2021) and this dissertation is that unlike this dissertation, they did not find evidence of sequence learning with random distractors (both for popout and non-popout targets). A methodological difference between our experiments that may have increased the likelihood of finding sequence learning was the exactness of the target sequence. In this dissertation, the target repeated exact locations whereas in Toh et al. (2021) experiments, it appeared in a repeating pattern of quadrants in which it could appear anywhere within the expected quadrant. Perhaps, when a target repeats exact locations this makes the signal less noisy and easier to learn. Although this kind of variability may occur in nature, this dissertation used exact locations because this is a stability one would likely experience when using a user interface. The discrepant finding between the two studies may also be due to random chance. Their data, at least numerically, followed a pattern consistent with disruption effects. Regardless, this dissertation showed evidence of sequence learning when searching an environment with a non-popout target and randomly changing distractors. If people can learn a sequence of target locations in this environment, this finding has several implications for the mechanism of sequence learning in visual search.

One possible reason sequence learning was found in all conditions, particularly environments with a non-popout target and random distractors, may be that participants were learning the button sequences not the sequence of target locations. This issue is a long debated problem in the SRT literature and studies specifically question if people can learn a sequence of target locations (Mayr, 1996; Willingham et al., 1989). There are multiple theories for what people are learning (Schwarb & Schumacher, 2012; Keele et al., 2003). But Toh et al. (2021) argued that people were learning the target sequence rather than the button sequence because they found no evidence of sequence learning in conditions with random distractors even though those conditions still contained the button sequence. They suggested that the random visuals disrupted learning the visual sequence of target locations. This dissertation, though, found evidence of sequence learning with random distractors. Perhaps participants in this dissertation were only learning button presses but an argument that participants ignored the visual search environments is unlikely. Participants's RT with non-popout targets were still in the range of serial search throughout the experiment indicating that they were likely still searching for the target. If they learned the sequence of buttons there would be little reason to search through the distractors. Even if they were looking at the search environment to confirm their learned button response, one would still expect RT to be much faster and perhaps more similar to RTs found with popout target. Without an eye tracker one cannot be sure where they were looking; maybe they spent the 1.5-2 seconds staring at the target to confirm that it was the target, but this seems unlikely. Participants seemed to be, on some level, attending to the search environments but what they were learning is unclear.

More recent SRT literature found that people can learn sequences of target locations but this learning does not occur when a button sequence is present and this is thought to be because both use spatial location resources (Eberhardt et al., 2017). If only one spatial sequence can be learned then only learning the directly useful motor sequence makes sense. However, in a task like visual search, someone could be learning the sequence of button presses or the sequence of eye movements. If people are learning a sequence of eye movements then the need to visually search and make random eye movements would weaken the signal to noise ratio. Additionally, a shared spatial resource pool suggests that the ability to learn any spatial sequence may be disrupted by processes that also use spatial resources. This possibility may have been why Willingham et al. (1989) did not show target location sequence learning. A shared resource pool might also mean that random eye movements to various spatial locations might interfere with learning any spatial sequence (button presses, eye movements, target locations). But in this dissertation, all environments, regardless of their visual search demands, showed evidence of sequence learning. Perhaps random eye movements can somehow be disregarded but how this spatial noise could be filtered is unknown. Perhaps the concept of a shared resource pool needs to be reconsidered. This theory comes out of the Dual-system model (Keele et al., 2003) which argues people can implicitly learn multiple sequences if they are in different dimensions but the definition dimensions was vague and further experiments exploring how different sequences interfere with each other is required. This dissertation shows that whether participants were learning target locations, button presses or something else, they were able to do so in various visual search environments including one where the distractors changed randomly.

One possible explanation for why eye movements did not disrupt sequence learning may be that there actually were few random eye movements. Over time, participants may have learned the transition probabilities that were present across all the SOC sequences in the experiment. In particular, a target would never appear in the same quadrant in a row and would only repeat the quadrant one before last once, halfway through a sequence repetition, thus often leaving only two quadrants to search through. However, participants still needed to search through these quadrants, three distractors each. Perhaps participants could use peripheral vision to look at more than one distractor at a time, but the area of these quadrants were larger than the functional visual field of 5-8 visual degree radius that could process multiple items at once (Wolfe, 2021) and some eye movements were likely required. Perhaps random eye movements were minimized to a sufficient degree so they did not interfere with learning the sequence of target locations. At the very least, this dissertation shows that people can learn a sequence of target locations in environments that initially require visual search before anything can be learned. Again, though, RT was consistent with serial search throughout the experiment, therefore, the need to search the distractors was likely not eliminated. An experiment with an eye tracker would be needed to confirm this idea.

Visual search demands not only increase the number of random eye movements, they also increase effort (Anderson & Lee, 2023) and increase time between targets. Either of these could have also disrupted sequence learning. A SRT study found that a 1500 ms response to stimulus interval diminished sequence learning (Frensch & Miner, 1994). In this dissertation, RT was near this range for the non-popout conditions and participants showed evidence of sequence learning indicating that the increased effort and this increased time did not interfere with sequence learning. Additionally, interval variability has been shown to disrupt sequence learning (Stadler, 1995) and, although not directly tested, participants likely did not find each target in the same exact amount of time on each trial. Thus, sequence learning is surprisingly robust in visual search given all the possible ways visual search is more difficult and complex than typical SRT tasks.

Another possible reason sequence learning was found across all experiments may be explicit awareness. If someone becomes aware that there is a sequence, they could consciously try to learn the sequence and enable sequence learning in environments that would otherwise not support implicit sequence learning. As mentioned before, sequence learning was not found when there was a 1500 ms interval between targets (Frensch & Miner, 1994). However, sequence learning was found with a 1500 ms interval when many participants were explicitly aware there was a sequence (Destrebecqz & Cleeremans 2003). In all experiments in this dissertation, over 50% of participants reported being aware of some kind of repeating target sequence. However, the number of participants who reported being aware did not differ between popout and non-popout conditions suggesting that the longer interval between trials did not encourage more explicit awareness. The number of participants who reported being aware was greater than Toh et al. (2021), perhaps this higher rate was due to the specific way the question was asked. Participants were asked, "While completing the previous search tasks, did the locations of where the T appeared ever occur in a repeating sequence?" and saying "ever" may have been too strong and vague a statement. However, noticing any kind of pattern could make someone more likely to search for patterns and to try to learn them. Similar to Toh et al. (2021), though, participants in this dissertation were unable to generate the sequence themselves. If participants were reporting they were aware of the 12 item sequence, this finding highlights the difference between their judgment informed by a sense of knowing and their structural knowledge as evidenced by an ability to generate the sequence on their own (Dienes, 2007).

Even if participants did not possess structural knowledge, perhaps a sense of knowing or any kind of awareness of target patterns also made sequence learning more likely. Therefore, differences in sequence learning were assessed depending on reported awareness. In this dissertation, those who reported being aware had a greater learning effect than those who reported being unaware. The learning effect is a combination of many possible aspects a participant could learn and this is not conclusive evidence that awareness impacted sequence learning. Additionally, participants who reported being aware may also be participants who are more attentive in general and so in general had better performance, not necessarily related to awareness or sequence learning. For the disruption effect there was also no conclusive evidence that reported awareness impacted sequence learning. These results, however, should be taken with a grain of salt. The sample size was insufficient to assess interaction effects between reported awareness and the target or distractor factors. Also, the sample size in some subgroups when assessing if participants who reported being aware and unaware had disruption effects significantly different from zero, were also less than the recommended sample size. Although these analyses are inconclusive, participants who reported being unaware sometimes had numerically smaller effects or, in the case of disruption effect, smaller or near zero particularly for the non-popout target and consistent distractors condition. These data warrants further investigation into the possibility that explicit awareness played a role in sequence learning. In general though, the current dissertation shows that across all six experiments, participants who reported being unaware of any target location pattern showed a learning effect and disruption effect significantly different from zero suggesting that explicit awareness is not, in general, required for sequence learning.

In the everyday world, though, people are highly likely explicitly aware that there will be regularities. In fact, using an interface where items move around randomly would be rather odd and annoying. Thus, even if sequence learning was only possible with explicit awareness, the results of this dissertation can still make implications for interface (re)designs. The findings suggest that the negative consequences in performance when interfaces update and change would occur in a variety of environments regardless of the findability of the target and the variability of the distractors. Future research could explore sequence learning with more interface looking search environments and with different kinds of sequences because SOC sequences are more complex than the sequence of button presses that occurs in everyday life.

This dissertation also made several predictions about sequence learning in environments that followed a consistent sequence of distractor contexts. The prediction was that sequence learning might be possible in this type of dynamically changing environment because it was changing predictably unlike conditions with random distractors. However, this dissertation found sequence learning with non-popout targets and random distractors as well. Dynamic environments in general seem not to interfere with sequence learning. Another possibility was that the presence of distractor context could prevent sequence learning because participants could have learned only the contexts to help them find the target. In contextual cueing studies, when there are two cues to predict a target's location, sometimes only one is learned (Endo, & Takeda, 2004; Kunar et al., 2014). Previous research showed that people could simultaneously learn a sequence of response identities (numbers) and learn familiar contexts (Jiménez, & Vázquez, 2011). However, that design means that the context predicted the location of the target and the sequence predicted the identity of the target (and the participants response). In the current dissertation, the context and the sequence both, redundantly, predicted the location of the target and, in contextual cueing, when there are redundant cues only one is learned (Endo, & Takeda, 2004). This dissertation showed that people can learn a sequence of target locations (or buttons) when the distractor context also predicts the target location. Because this dissertation did not directly test contextual cuing, it cannot speak to whether participants learned the contexts.

Additionally, learning the distractor contexts could have prevented the expression of sequence learning for the disruption effect. When the sequence is reordered, the targets are still in the expected locations predicted by the context and participants could use their familiarity with the context to find the target. This dissertation found a significant disruption effect for conditions with distractor context indicating that participants had learned the sequence and were slower when the target did not occur in the expected location at the expected time. Participants were likely also learning the contexts and this learning could have minimized the disruption effect in these conditions compared to the other conditions but the effect was not eliminated. To fully understand the impacts of target location sequence learning, contextual cueing, and learning a sequence of contexts requires an experiment directly separating these aspects apart (an experiment investigating this issue was included in the original plan for this dissertation but was cut for time). However, this dissertation provides an important initial first step in showing that sequence learning is present in visual search environments (which is often the case for contextual cueing studies) and in environments with a sequence of distractor contexts.

Do Some Environments Support Sequence Learning More Than Others?

The main interest of this dissertation was to assess the presence of sequence learning in various environments but, as an initial exploration, the measures of sequence learning were also compared across experiments. Between popout and non-popout targets, there was a greater learning effect and a greater disruption effect for non-popout targets. This difference is likely due to the added benefit of knowing where to find a target rather than an indication of greater amounts of sequence learning. Also, the learning effect was likely greater in the conditions with a non-popout target because there was more room to improve whereas conditions with a popout target were possibly limited by a floor effect and participants RT could not become any faster. For the different distractor types, this dissertation did not find conclusive evidence that different distractor environments had more or less sequence learning. There was some evidence that there was a greater learning effect for static vs random distractors but again, the learning effect is composed of multiple aspects a participant could learn. Furthermore, the analysis that showed this difference was collapsing across popout and non-popout targets and whether this was done or (could be done) in an accurate way given how different these two conditions' RT are, is unclear. In the uncollapsed analysis, the non-popout conditions showed this numerical trend but it was not significant. Thus, in general, the different search environments seemed to result in similar amounts of sequence learning but future research will be needed to confirm this possibility.

One distractor type that was hypothesized to have greater sequence learning than static distractors was the sequence of contexts. In these environments there are multiple cues to target location, the prior target locations, the current context of distractor locations, and the prior context of distractors, the first and last of which are sequence related. In theory these two sequence regularites might combine and allow for even greater sequence learning than when only one is present. In the SRT literature, when there are multiple possible types of sequences that can be learned, the effect on RT is larger than when there is a single sequence (Keele et al., 1996). According to the Dual-system model, learning both sequences seems to require the two types of sequences to be different types such as one location based sequence and one feature based sequence (Keele et al., 2003). The condition with a popout target and a sequence of contexts may have shown greater sequence learning because literature on contextual cueing suggested that these contexts are learned as a global configuration (Ogawa & Kumada, 2008) which may be similar to learning a shape feature. Furthermore, this dissertation found many participants in popout conditions relied on peripheral vision search strategy and global configuration learning is found in contextual cuing studies that restrict eye movements (Zinchenko et al. 2020). If a sequence of contexts with a popout target could be learned as a sequence of features this leaves spatial resources available to learn the sequence of target locations (or some other spatial sequence). However, this dissertation did not find evidence of greater sequence learning in the context conditions compared to the static conditions. There are many possible reasons this prediction was not found. For one, how a global configuration would be classified in the dual-system model is not clear. Perhaps global configurations require spatial resources rather than as an overall shape feature. Additionally, the disruption effect may not have fully captured the full effect of both sequences being disrupted because, when the sequences are in the unlearned order, the current distractor context still predicts the location of the target. The context could allow participants to quickly find the target, in general, or find it after the target was not in the expected sequence location. Thus, there are many factors that limit this dissertation's ability to compare across conditions and, in regards to the context sequences, a follow up experiment assessing possible combined effects of learning a sequence of target locations, contexts, and a sequence of contexts is required.

Summary And Conclusions

This dissertation assessed sequence learning in a variety of search environments and found sequence learning across all the conditions tested suggesting that sequence learning is robust in visual search. This finding directly counters Toh et al. (2021) who claimed that sequence learning is fragile in visual search. Unlike Toh and colleagues' findings and claims, distractors can be changing and this noise does not disrupt sequence learning. This dissertation's findings provide a critical step in better understanding the nature of sequence learning and calls into question the idea that spatial sequence learning relies on a single shared pool of resources. Furthermore, sequence learning occurred in visual search environments despite the increased effort, time, and variability present in visual search compared to the traditional SRT task. This research opens the door to many avenues of future research on sequential visual search. Future research could more specifically explore how contextual cueing interacts with sequence learning. Future research could also explore how more everyday contexts like user interfaces impact sequence learning. Currently this dissertation's findings indicate that people are highly sensitive to learning visual search sequences and these expectations can lead to disruptions in performance in a variety of settings. These findings suggest that when an interface updates and items are not located when and where they are expected, people may struggle to accomplish their tasks.

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