The interaction between visual resolution and task-relevance in guiding visual selective attention

by

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B.S., University of Wisconsin – La Crosse, 2012
M.S., Kansas State University, 2016

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Psychological Sciences
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Abstract

Visual resolution (i.e., blur or clarity) is a natural aspect of vision. It has been used by film makers to direct their audience's attention by focusing the depth of field such that the critical region in a scene is uniquely clear and the surrounding is blurred. Resolution contrast can focus attention towards unique clarity, as supported by previous eye tracking and visual search research (Enns & MacDonald, 2013; Kosara, Miksch, Hauser, Schrammel, Giller, & Tscheligi, 2002; & McConkie, 2002; Peterson, 2016; Smith & Tadmor, 2012). However, little is known about how unique blur is involved in guiding attention (e.g., capture, repel, or be ignored). Peterson (2016) provided reaction time (RT) evidence that blur is ignored by selective attention when resolution is not task-relevant. Perhaps visual resolution is a search asymmetry where unique clarity can be used to guide selective attention during search, but unique blur cannot guide attention. Yet, perhaps the RT evidence was not sensitive enough with Peterson's (2016) methodology to observe unique blur capturing or repelling attention. Eye movements (e.g., letter first fixated) may be more sensitive than RT as it measures blur and clarity's influence on guiding attention earlier in a trial.

The current study conducted three experiments that investigated: a) how visual resolution guides attention when it is task-irrelevant (Exp. 1), b) whether visual resolution is a search asymmetry, by manipulating resolution's task-relevance (*Use Blur*, *Use Clarity*, *Do Not Use Unique Blur or Clarity*, & *No Instructions*) (Exp. 2), and c) whether blur and/or clarity are processed preattentively or require attention (Exp. 3). Experiments 1 and 2 manipulated blur and clarity (Exp. 1 Resolution = Task-*irrelevant* & Exp. 2 Resolution = Task-*relevant*), during a rotated L and T visual search measuring RT and eye movements. Experiment 1 found with the more sensitive eye movement measures that unique clarity strongly captured attention while unique blur weakly repelled attention towards nearby clarity (or clarity, especially that close to blur, captured attention). Experiment 2 found evidence that visual resolution is not a search asymmetry because the influence of resolution on selective attention was contingent upon its task-relevance, which theoretically supports the presence of a reconfigurable resolution feature detector. Experiment 3 used a feature search for either blur or clarity (i.e., resolution was task-relevant) and compared RT x Set Size search slopes. Both blurred and clear target present RT x Set Size search slopes were ~ 1 msec/item. The results strongly supported that blur and clarity

are both processed preattentively, and provided additional evidence that resolution is not a search asymmetry.

Overall, the current studies shed light on how visual resolution is processed and guides selective attention. The results revealed that visual resolution is processed preattentively and has a dynamic relationship with selective attention. Predicting how resolution will guide attention requires knowledge of whether resolution is task relevant or irrelevant. By increasing our understanding of how resolution contrast guides attention, we can potentially apply this knowledge to direct viewers' attention more efficient using computer screens and heads-up displays.

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Dedication

I dedicate this work to my loving wife, Carrie. It is through your love, support, and motivation that I have been able to achieve my goals. You are my rock. Always and Forever.

Chapter 1 - The Interaction between Visual Resolution and Task-Relevance in Guiding Visual Selective Attention

Visual resolution is a natural aspect of vision that guides visual selective attention. We naturally desire our visual experience to allow us to view a clear, crisp world around us. However, the counterpart to visual clarity, visual blur, is also present during our visual experience. Blur is commonly encountered as we interact with our environment. For example, if you are focused on reading a book and you bring it sufficiently close to your eyes, the text will appear blurry until your lenses accommodate to the book's new depth. This will allow you to continue reading with the text perceived clearly. Thus, resolution changes based on the viewer's focus within their depth of field. Accommodation is used by the visual system, when possible, to adjust the resolution of fixated objects in the visual field.

The perception of blur can occur in several different ways. Blur can be directly caused by environmental stimuli such as global luminance statistics, local luminance contrasts, or spatial frequency information (O'Hare & Hibbard, 2013). For example, the edges of a shadow from an object will have decreasing high spatial frequency information as the cast of the shadow increases. Which objects are blurry in a viewer's visual field are heavily contingent upon the viewer's current depth-of-focus (Ciuffreda, Wang, & Vasudevan, 2007). The measurement of geometric blur as a statistical regularity involves a viewer's depth-of-focus and an object's depth relative to the viewer's depth-of-focus (Held, Copper, & Banks, 2012). Therefore, an object can be perceived as blurry or clear depending on where it is located relative to the viewer's depth-of-focus. How blurry an object is perceived also depends on what region of the retina is processing the object. The fovea can resolve the highest spatial frequency information, which then decreases as information moves out into the periphery (Loschky, Ringer, Johnson, Larson, Neider, & Kramer, 2014). Across the retina there are decreasing thresholds for what level of higher spatial frequency information is needed to have the subjective experience of seeing that part of the world on your retina clearly. A threshold for clarity is reached when the full range of perceptible spatial frequency information is present at a given retinal eccentricity. Blur is perceived when there is a lack of relatively higher perceptible spatial frequency information at a given retinal eccentricity (Loschky, McConkie, Wang, & Miller, 2005; Loschky et al., 2014).

Retinal image blur can occur from target blur, where the object in the environment is blurry (e.g., an out-of-focus picture, fog, shadows, etc.), or defocus blur, which occurs when the object's light vergence is defocused on the retina (e.g., refractive errors). Both target blur and defocus blur have been shown to illicit accommodation (Phillips & Starks, 1977), being used as depth cues[1]. Campbell and Westheimer (1960) have shown that on average an accommodative response to focus on a target begins ~370 msec after the onset of the target. This suggests that blur is useful early in the visual system to allow accommodative responses to blur. Accommodation is controlled by the autonomic nervous system (Olmsted, 1944), which suggests that attention does not play a major role in blur processing for accommodation. The visual system can make accommodative responses without conscious influence (Toates, 1972). Yet, the goal of accommodation is to make objects in the fovea appear clearly. Therefore, visual resolution may be very useful in guiding attention. For example, film makers have used resolution in film to direct their audience's attention to where the director wants them to look (i.e., attend) during scenes. When two people are talking in a scene, a technique called *racking focus* can be used to make the individual speaking appear clearly and the listener appear blurry with the audience's attention meant to move to the clear speaker. Once the roles reverse (i.e., the speaker becomes the listener and vice versa), then the resolution also changes so the movie

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[1] Blur is a normal part of vision that we can use as a depth cue. Held et al. (2012) investigated blur as a depth cue in comparison to disparity. Disparity is considered one of the most useful depth cues, but moving away from the fixation point disparity's usefulness reduces quickly. However, blur which can also be used at the point of fixation, which is where the eyes are focused in the depth of field, is consistent moving further away from the point of fixation. This results in a viewer relying on blur information to judge depth over disparity depth cues once objects are no longer located near the point of fixation (Held et al., 2012). Blur as a depth cue does change though moving further into the periphery, when focused on the fixation point objects that are nearby, whether slightly in front of or behind the exact location of the fixation point will be perceived clearly because they will be within the *zone of clarity* (Ciuffreda et al., 2007). The *zone of clarity* is a region where if there is adequate low-level visual information, such as high spatial frequency information available, then objects will be perceived clearly. This zone increases with increasing eccentricity, such that an object a certain distance from the point of fixation at the fovea may be consciously perceived as blurred, while the object under the same conditions further into the periphery may be perceived as clear (Ciuffreda et al., 2007). Using blur as a depth cue may guide vergence eye movements (Held et al., 2012), and accommodation (Ciuffreda et al., 2007), to allow for selected objects or regions to be seen more clearly.

viewer's attention moves to the new speaker. To use this technique well, the resolution changes should go unnoticed by the audience, but still influence where they attend in the scene. Though film makers have long used resolution to guide attention in this way, it is not fully understood how resolution guides attention. A greater understanding of how resolution can be used to guide attention may allow its use to be enhanced. For example, this knowledge could be used in developing heads up displays or computer screens that incorporate software that can direct the viewer's attention efficiently to critical information using resolution contrast.

Visual Resolution and Attention

Previous eye tracking studies and visual search studies have investigated the influence resolution has on visual selective attention, which have commonly found evidence that unique clarity captures attention whether it is task-relevant (find the clear target) or -irrelevant such as during free-viewing of a scene (Enns & MacDonald, 2013; Kosara, Miksch, Hauser, Schrammel, Giller, & Tscheligi, 2002; Loschky & McConkie, 2002; Peterson, 2016; Smith & Tadmor, 2013; Veas, Mendez, Feiner, & Schmalsteig, 2011). Conversely, blur is typically ignored (neither repelling nor capturing attention) (Enns & MacDonald, 2013; Peterson, 2016; Smith & Tadmor, 2013), or actively avoided by attention (Loschky & McConkie, 2002).

Peterson (2016) has shown that when blur and clarity are manipulated to be non-predictive of the target location in a rotated L and T visual search task, then clarity captures attention and blur is ignored by selective attention. This is based on the finding that a clear target singleton's RT is much shorter than when all the letters are blurred or clear, but a blurred target singleton's RT is very similar to when all the letters are blurred or clear. Enns and MacDonald (2013, Exp. 3) found similar results by having participants free view a scene having uniquely blurred or sharp regions compared to uniformly blurred or sharp scenes. They compared uniquely sharp regions to uniquely blurred regions and found that the mean first fixation latencies were shorter for uniquely sharp regions and, likewise, the mean frequency of fixations were higher, suggesting attraction to the uniquely clear regions. Conversely, the uniquely blurred regions did not significantly differ from the uniformly blurred or sharp scenes, which also did not significantly differ from each other, suggesting that unique blur was not neither capturing, nor repelling attention, but was ignored by attention. Nevertheless, there was a non-significant trend that uniquely blurred regions attracted more repeated fixations compared to the same region when the scene was uniformly blurred. Both the Peterson (2016) and Enns and MacDonald (2013) findings primarily support the hypothesis that when blur is task-irrelevant it does not capture, nor repel attention, but it is ignored by attention.

Visual Resolution and Saliency

Peterson's (2016) blurred and clear target singleton RT results are also similar to what Braun (1994) found when comparing targets that were configured to have maximum or minimum saliency differences within a dimension (e.g., a bright singleton amongst dim non-singletons = maximum saliency; a dim singleton amongst bright non-singletons = minimum saliency). Braun found that with a dual-task paradigm, when attention was allocated to a central task, performance on a peripheral task for maximum saliency conditions was less affected than the low saliency conditions. While Peterson (2016) did not include a dual-task paradigm, the results are similar to Braun (1994) because the clear target singletons seem to be similar to maximum saliency conditions, and blurred target singletons are more like the minimum saliency conditions. However, there is an important difference to note between Braun (1994) and Peterson (2016), which is that the latter found no significant difference in RT between the all-blurred and blurred target singleton conditions. Conversely, Braun's minimum salience condition without visual attention remained above chance. This was explained by possibly having some discriminability of the minimum salience target from the maximum salience distractors, or that there was still some residual visual attention available despite carrying out their concurrent task. Either way, this would suggest that Peterson (2016) should have found that a blurred target singleton's RT was faster than the all-blurred condition's RT. Interestingly, Enns and MacDonald (2013, Exp. 3) included findings that were not significant, but showed a trend that unique blur may have weakly captured eye movements. Perhaps including eye movements in Peterson's (2016) methodology would allow for a more sensitive measure than RT to detect resolution's influence on attention early on in a trial. Eye movements can measure attentional changes earlier in the trial by observing what item is first fixated in each trial, whereas RT only provides the time it took to make a response at the end of the trial.

Enns and MacDonald (2013, Exp. 3) argued that blur is not actively avoided. However, the RT evidence from Peterson (2016) strongly suggests that unique clarity captures attention. Unique clarity is created by having resolution contrast between blur and clarity. Furthermore, not only must blur be present for unique clarity to exist, but blur must also be perceived as being different from the unique clarity in order for the unique clarity to capture attention. If this difference is not perceived, then there is no perceived resolution contrast and no guidance of attention, as shown by the fact that RTs in Peterson's All blurred/clear conditions did not significantly differ. Therefore, blur is an integral aspect of what allows unique clarity to capture attention. Thus, if unique clarity is capturing, then it seems plausible that unique blur must also be repelling. However, neither Enns and MacDonald (2013, Exp. 3) nor Peterson (2016) has shown evidence of blur repelling attention, though it is still theoretically plausible.

Blur has been shown to be visually discomforting (Juricevic, Land, Wilkins, & Webster, 2010; O'Hare & Hibbard, 2013). Juricevic et al. (2010) found that strong luminance blurring created the greatest discomfort. O'Hare and Hibbard (2013) found removing high spatial frequencies from circular gratings creates the perception of blur, and was judged more visually discomforting. If blur repels attention from its spatial location it may be in response to discomfort, similar to pulling your hand back away from a fire when it is too close. Repelling attention from a blurred location may be a response mechanism to avoid visual discomfort from a blurred stimulus. Interestingly, like fire at a correct distance can provide warmth, perhaps blur can also be useful under certain circumstance, possibly when blur is useful in completing a task.

By including the more sensitive measure of eye movements in a more controlled experimental setting than Enns and MacDonald (2013, Exp. 3), it may be possible to find evidence that blur repels attention. Enns and MacDonald (2013, Exp. 3) manipulated resolution in scenes, but the task was still to view the images for a memory task later. Instead, by using Peterson's (2016; Exp. 2) visual search methodology there would be greater control in the method to measure the influence resolution has on attention through eye movements.

Experiment 1 will investigate whether eye movements can reveal an early influence of visual resolution in terms of both blur and clarity in guiding visual selective attention. If unique blur captures attention, it should be the first letter fixated at an above-chance rate (Chance = 1/Set Size). If unique blur repels attention, then it should be the first letter fixated at a below-chance rate. Finally, if unique blur is ignored, then it should not influence the search and it should be the first letter fixated at the chance rate.

Visual Resolution and Search Asymmetry

Peterson's (2016) results are possibly explainable in terms of visual resolution being a search asymmetry. Braun (1994) also explained part of his results as potentially being due to the min and max salience stimuli being a search asymmetry. Search asymmetries occur when the distinction between which visual features are used for the target versus the distractors heavily influences search results. For example, Treisman and Souther (1985) have shown evidence of a search asymmetry where searching for a Q amongst O distractors was much faster than searching for an O amongst Q distractors. Searching for the presence of a critical feature (the line attached to the circle in "Q"), produced an efficient search (pop-out of the Q among Os), while the absence of the critical feature (the absent line in "O"), produced an inefficient serial search (searching one or a few items at a time to find the target), suggesting attention was necessary (Treisman & Gelade, 1980).

Another search asymmetry from Treisman and Gormican (1988) is searching for a target amongst distractors sharing a similar property but differing in the amount of that property. Therefore, it need not be the presence or absence of a critical feature, but rather a quantitative difference of the critical feature between the target and distractors. For example, a dark grey target dot amongst light grey distractor dots on a white background was searched for efficiently, while flipping the target-distractor greyness values produced inefficient search. Treisman and Gormican's findings with dark and light grey dots on a white background aligns with Braun's (1994) findings of maximum versus minimum salience stimuli. Peterson (2016) defined clarity as having the full range of perceptible spatial frequency information and blur as a lack of the relatively higher range of perceptible spatial frequency information. Thus, the critical feature may be the unique high perceptible spatial frequency information being present for clarity and absent for blur. Peterson's resolution findings may also be explained similar to maximum versus minimum salience (e.g., dark vs. light grey dots), where the amount of spatial frequency information that is present is driving what appears to be a search asymmetry for Peterson's resolution findings. Yantis and Egeth (1999) have shown that features on a prothetic dimension can capture attention when task-irrelevant. A prothetic dimension contains features that range on a quantifiable continuum such as size or luminance. Visual resolution may be a feature on a prothetic dimension, which ranges from only low spatial frequency information to having the full range of perceptible spatial frequencies. This would result in the opposing ends of the visual resolution continuum being blur on one end and clarity on the other.

Unfortunately, the results of Peterson (2016) cannot differentiate whether resolution is a search asymmetry or not because resolution was task-irrelevant. When Treisman and Souther (1985) showed that the search for an O target amongst Q distractors produced an inefficient search, finding the O target was the task. On the other hand, in Peterson (2016), blur and clarity were task-irrelevant—the task was to either respond whether the T was present or absent, or respond whether the T was pointed to the left or the right. Participants were never told to look for a blurred or clear T as the resolution was uninformative of the location of the T target. Interestingly, Enns and MacDonald's (2013) Experiment 4, showed that when blur was task-relevant, then blur did capture attention. Interestingly, in that experiment both unique blur and clarity were task-relevant, because participants needed to determine which side of an image had a unique target region that was either blurred or sharp in comparison to the rest of the image. They found that unique blur was more quickly and accurately detected than the unique clear target regions. Thus, resolution may not be a search asymmetry, but instead resolution's influence on attention may be contingent upon resolution's task-relevance.

In sum, to investigate the possibility that visual resolution is a search asymmetry, blur and clarity need to be made task-relevant. If visual resolution is a search asymmetry, then the search for a blurred target should be inefficient even when blur is task-relevant. However, if the search for a blurred target becomes efficient when blur is task-relevant, then visual resolution is not a search asymmetry, but rather blur's effect on attention is contingent upon it's task-relevance. The clear target is expected to be efficiently searched for when clarity is task-relevant because Peterson (2016) has already shown it to capture attention when task-irrelevant. In Experiment 2, visual resolution will be made task-relevant by manipulating instructions and the probability of the task-relevant resolution (i.e., blur or clarity) being predictive of the target location.

Search asymmetries have been used to investigate and better understand basic visual features and their influence on visual attention (Wolfe, 2001). Unique clarity has been argued to be processed preattentively (Kosara et al., 2002). It is possible that Experiment 2 may find that blur cannot be used to guide search even when task-relevant, while clarity can guide attention when task-relevant. However, it is also possible that when blur is made task-relevant that blur will be able to guide attention. If blur can guide attention when task-relevant, then the question becomes whether blur is processed preattentively or requires attention. Loschky et al. (2014) has already shown evidence that blur detection is unaffected by cognitive load using a dual-task paradigm. Therefore, blur may be processed preattentively. Also, Webster, Georgeson, and Webster (2002) have shown blur adaptation such that viewing a blurred image and then being shown the original unblurred version of the image made the unblurred image appear sharper, whereas viewing a sharpened image and then being shown the original unsharpened version of the image made the unsharpened image appear blurrier. This suggests that blur and clarity may be part of one featural dimension called resolution. If so, then if clarity is processed preattentively (Kosara et al., 2002), then it is possible that blur too is processed preattentively. If a search asymmetry is present, the theoretical implication is the existence of a basic feature detector for resolution. Based on previous literature, it appears that a resolution feature detector is biased to focus attention toward clarity (Enns & MacDonald, 2013; Kosara et al., 2002; Loschky & McConkie, 2002; Peterson, 2016; Smith & Tadmor, 2012). A fixed resolution feature detector that is biased towards clarity could also be simply thought of as a clarity feature detector. Yet, a resolution feature detector may be reconfigured to other regions of the resolution spectrum, therefore not fixed, based on Enns and MacDonald's Experiment 4 finding that unique blur when task-relevant was fixated more quickly and accurately than unique clarity. It may be that there is a reconfigurable resolution feature detector, which typically guides attention towards nearby clarity, unless blur is task-relevant. If making blur task-relevant does not result in selecting blur more quickly and accurately, then that would be evidence that the resolution feature detector is fixed and not reconfigurable by top-down influences to different ranges of the resolution spectrum. It is then also possible that there is no resolution feature detector at all. Previous literature has already suggested that there is sensitivity to select unique clarity, which suggests that at a minimum there is at least a fixed resolution feature detector that favors clarity over blur. Whether the resolution feature detector is fixed or reconfigurable is what is in question.

Experiment 3 will investigate whether blur and clarity are processed preattentively. In addition to the absence of dual task effects, the other typical way to investigate and provide evidence whether a feature is processed preattentively or requires attention is by using a feature search and measuring RT x Set Size search slopes (Treisman & Gelade, 1980). A feature search could be performed to determine the presence or absence of a blurred target amongst clear distractors while varying set size. This would allow for the RT x Set Size search slopes to be analyzed, such that if the slopes are near zero, that would be evidence for preattentive processing, whereas slopes of ~20-30 msec/item would suggest that attention is required (Treisman & Gelade, 1980; Wolfe, 2007).

Research Questions

1. Does task-irrelevant blur actively capture or repel selective attention, or is it passively ignored by selective attention?
2. Is visual resolution a search asymmetry?
3. Are blur and/or clarity processed preattentively or do they require attention?

Resolution Guides Selective Attention - Competing Alternative Hypotheses

There are three competing alternative hypotheses, which originate from Peterson (2016). The three hypotheses are *Blur Captures*, *Blur Repels*, and *Blur is Ignored*. Figure 1 shows the three competing alternative hypotheses as predicted with reaction time. Figure 2 displays the three competing alternative hypotheses as predicted by eye movements. The three competing alternative hypotheses stated in Peterson (2016) and restated here predicted the following:

1) *Blur Captures:* Attention is drawn to contrast between clarity and blur, and this contrast is maximized for both blur and clear singletons.
2) *Blur Repels:* Blur only repels attention in contrast to clarity, and clarity only captures attention in contrast to blur.
3) *Blur is Ignored:* Blur is ignored by attention regardless of whether there is blur/clarity contrast, and unique clarity captures attention only in contrast to blur.

Chapter 2 - Experiment 1: Eye Movements in Visual Search when Resolution is Task-irrelevant

The purpose of Experiment 1 is to investigate the influence resolution has on selective attention early on in a trial. The current experiment is an extension of Peterson (2016) Experiment 2 by including eye tracking. Peterson's RT results indicated that unique clarity captures attention, while unique blur was ignored by selective attention. As in Peterson (2016), the RT data was analyzed to support one of the competing alternative hypotheses (e.g., captures, repels, or is ignored). The quantitative hypotheses from Peterson (2016) were also used to analyze the RT data. However, if unique blur weakly repels or captures attention, the RT results may not be a sensitive enough measure to detect the influence blur has on selective attention. Therefore, this experiment included eye tracking to measure how often the resolution singletons were fixated as the first item. This is a more sensitive measure than RT because it measures blur and clarity's influence on attention earlier in a trial because there is less time for other factors to influence search. Whereas, RT is a measure of blur and clarity's influence on attention, which is collected at the end of a trial, and may be more influenced by other factors during search. Unique blur's influence on guidance attention was also measured based on which item number the blurred target was fixated on during the blur target singleton and All Blur trials.

Reaction Time Hypotheses

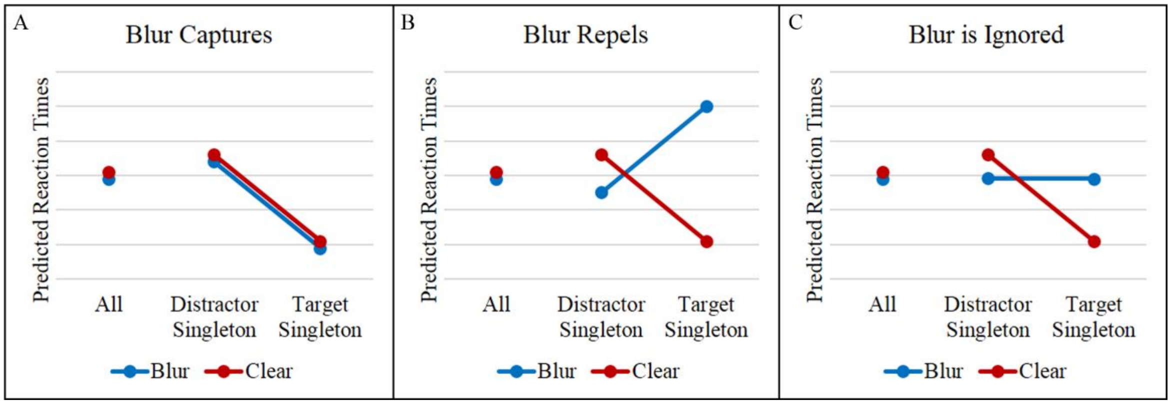

Figure 1. Generalized competing alternative hypotheses for reaction time is based on predicted average number of items searched. All hypotheses predict when there is no resolution contrast, then selective attention will not be guided by blur and clarity. Therefore, all-blurred and all-clear are predicted to be the same in all hypotheses (A-C). Unique clarity is expected to capture attention in all hypotheses. When unique clarity is at the target, RTs are faster and when it is at a distractor, RT is slower. The three competing alternative hypotheses differ based on the blurred target and distractor singleton conditions. A) *Blur Captures* predicts faster RTs when unique blur is at the target, but slower RTs when it is at a distractor location, because blur is capturing attention and directing it away from the target. B) *Blur Repels* predicts slower RTs when the target is uniquely blurred, repelling attention away from the target, and faster RTs when a distractor is the uniquely blurred item because attention is more likely to select that target earlier. C) Blur is Ignored predicts that unique blur will not influence selective attention. Therefore, whether blur is unique or uniform the RTs should be similar. Note: All-blurred and all-clear conditions are predicted to have overlapping RTs, they are only offset for ease of displaying the RT predictions.

Assumptions of the Quantitative Models

The quantitative model predictions follow the same assumptions as stated in Peterson (2016) and restated here:

1. Search (for the rotated T among rotated Ls) is serial with one or a few items processed at a time.
2. When there is no blur/clarity contrast, therefore no attentional guidance, search for the target is random.
3. A unique item that captures attention will have the highest probability of being the first item attended.

4. A unique item that repels attention will have the highest probability of being the last item attended.
5. A unique item that is ignored by attention will be included in random search.
6. There is perfect memory for previously searched items.

As noted in Peterson (2016), these assumptions are certainly over-simplified. However, by making these simplified assumptions, the general relationship for each of the competing hypotheses can be calculated. Table 1 displays the hypothesized average items searched, calculated using the assumptions above with a minimum possible search of 1 and a maximum search value equal to the set size (See Peterson, 2016 [Appendix 1] for detailed calculations and explanations for set sizes 4 & 8; see Appendix 1 for detailed calculations for set size 6).

Table 1

Experiments 1 & 2 Competing Hypotheses' Average Number of Items Searched for *Resolution x Condition*

		Blur Captures			Blur Repels			Blur is Ignored		
		Exp. 1		Exp. 2	Exp. 1		Exp. 2	Exp. 1		Exp. 2
Resolution	Condition	SS: 4	SS: 8	SS: 6	SS: 4	SS: 8	SS: 6	SS: 4	SS: 8	SS: 6
Blurred	All	2.5	4.5	3.5	2.5	4.5	3.5	2.5	4.5	3.5
Blurred	Far	3	5	4	2	4	3	2.5	4.5	3.5
Blurred	FarMid	-	5	-	-	4	-	-	4.5	-
Blurred	Mid	3	5	4	2	4	3	2.5	4.5	3.5
Blurred	Near	-	5	4	-	4	3	-	4.5	3.5
Blurred	Target	1	1	1	4	8	6	2.5	4.5	3.5
Clear	All	2.5	4.5	3.5	2.5	4.5	3.5	2.5	4.5	3.5
Clear	Far	3	5	4	3	5	4	3	5	4
Clear	FarMid	-	5	-	-	5	-	-	5	-
Clear	Mid	3	5	4	3	5	4	3	5	4
Clear	Near	-	5	4	-	5	4	-	5	4
Clear	Target	1	1	1	1	1	1	1	1	1

Note. SS = Set Size. Resolution refers to whether the singleton or all letters were presented clearly or blurred. Condition refers to the relative distance from the unique item to the target (e.g., Blurred Far is when the item farthest from the target is the only blurred item). The All conditions have no resolution contrast, with all letters being either blurred or presented clearly.

Eye Movement Hypotheses

The three competing alternative hypotheses for eye movements are based on whether unique blur causes attentional capture, repulsion, or is ignored. Evidence to support or refute these hypotheses can be collected by measuring whether the first item fixated in a trial is the singleton (Singleton conditions only, excluding the All conditions). Importantly, this measure is for the first letter fixated, not necessarily the first fixation, as the first fixation may or may not be located at a letter. Thus, the measure is used to investigate which letter is looked at first compared to chance levels, where chance is 1/Set Size.

1) Capture: The singleton is the first letter fixated at a higher than chance rate.
2) Repel: The singleton is the first letter fixated at a lower than chance rate.
3) Ignored: The singleton is the first letter fixated at an equal to chance rate.

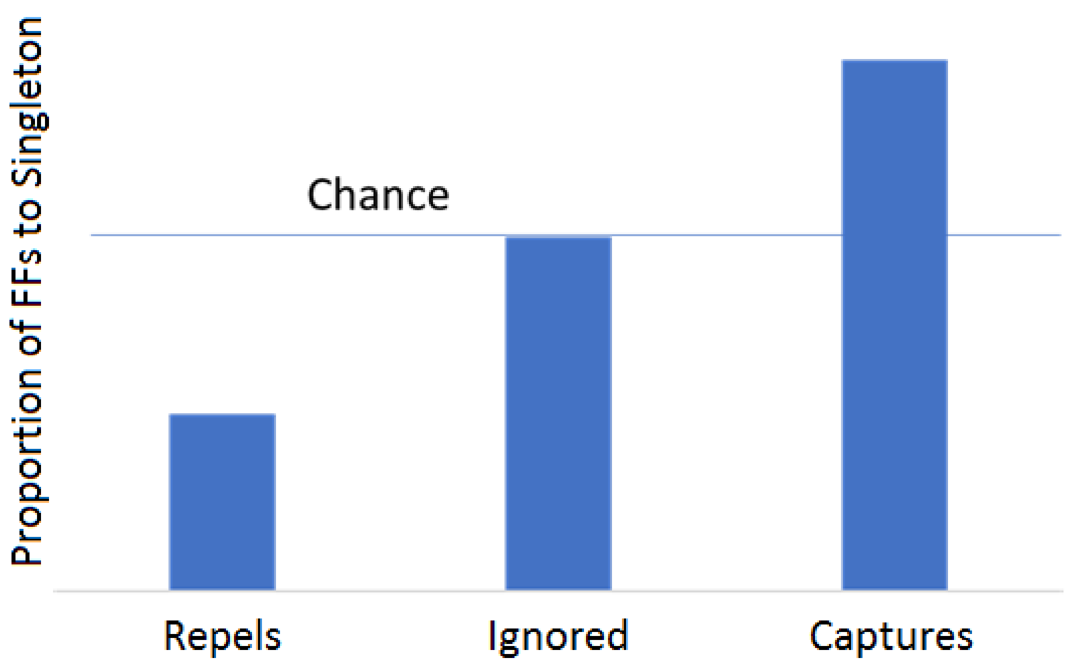

Figure 2. Predicted proportion of first fixations (FFs) to a singleton based on each of the three competing alternative hypotheses. If the singleton repels attention, then the proportion of FFs to the singleton should be less than chance. If the singleton is ignored by attention, then the proportion of FFs to the singleton will be equal to chance. If the singleton captures attention, then the proportion of FFs to the singleton is expected to be higher than chance. Chance is equal to 1/Set Size.

Figure 3 shows the three competing alternative hypotheses for eye movements based on when a blurred target singleton is fixated during search. The three competing alternative hypotheses are based on whether unique blur's influence on attention is capturing, repelling, or is ignored. We can find support for one of the three competing hypotheses by comparing the item number a blurred target is fixated on for the blurred target singleton trials to the All Blurred trials.

1) Captures: The blurred target will be fixated more often as the first item and less often as the last item during search in the Blurred Target Singleton trials than the All Blurred trials.

2) Repels: The blurred target will be fixated less often as the first item and more often as the last item during search in the Blurred Target Singleton trials than the All Blurred trials.

3) Ignored: The blurred target will be fixated equally often during search in the Blurred Target Singleton trials as the All Blurred trials.

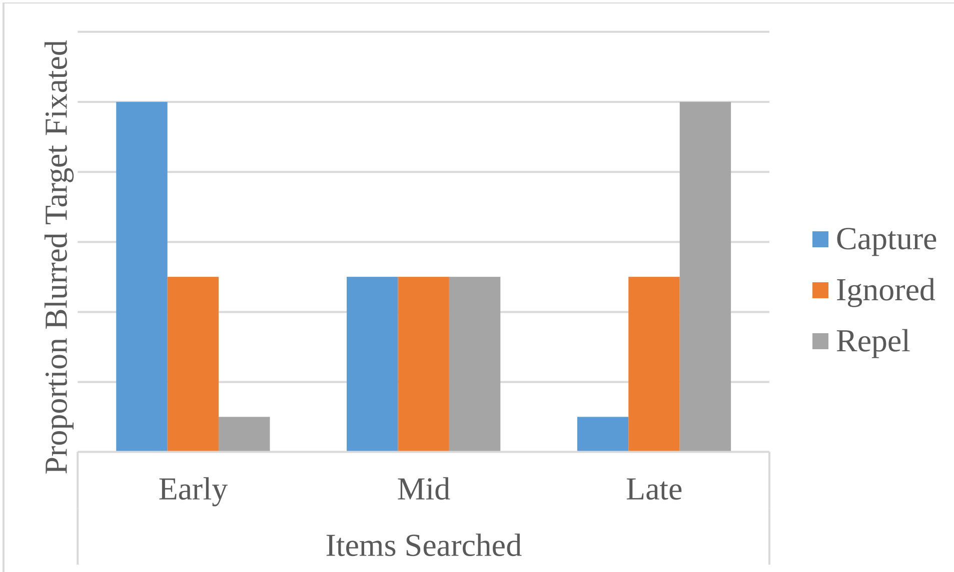

Figure 3. Predicted proportion of the blurred target being fixated at either early, mid, or late items during a search. Each of the three competing hypotheses are represented at each stage of search. Early, mid, and late are used for the prediction graph because it can be generalized to the set sizes of 4, 6, and 8. For example, early for a set size of 4 may only represent the first item being searched, while at set size of 8 it may refer to the first two items being fixated during search. The prediction is relative to the number of items searched. However, the greatest differences are expected to be shown between the first and last item of each set size.

As a preliminary point, it is important to explain the rationale for the set size manipulation used in this experiment. As in Peterson (2016), the set sizes of four and eight were not included for the typical reason in a visual search study, namely to test for efficient versus inefficient search. Instead, using a rotated L versus T search task, which is well known to be very inefficient (Julesz & Bergen, 1983; Egeth & Dagenbach, 1991), the reason that set size was varied was to see if the larger set size would create an even stronger attentional effect for the task-irrelevant manipulation. Therefore, in the analyses for this experiment there is no comparison of search slopes between set sizes, since it is already assumed that the search is inefficient in both set sizes. Instead, each set size serves as a replication of the other, and it is hypothesized that the stronger effects of task-irrelevant resolution on attentional selection will be in the larger set size, due to increased demand for attention in that condition.

Method

Participants

There were 55 participants from Kansas State University's Psychological Sciences undergraduate research pool (46 females, mean age = 20.28). Participants' vision was 20/30 or better. All participants were naïve to the purpose of the experiment. Study procedures were approved by Kansas State University's Institutional Review Board, and all participants gave their informed consent prior to completing the study, which they received class credit for.

Apparatus

The experiment was conducted on two eye trackers. One used an Origin Genesis PC running Microsoft Windows 7 Ultimate, with an Intel Core i7 970 processor (3.2 GHz), 24 GB DDR3 RAM, 2 GB Radeon HD6950 video card, and Creative SB X-Fi sound card, which was connected to an EyeLink 1000 eye tracker. The other used a SilverStone PC running Microsoft Windows 7 Ultimate, with an Intel Core i7 4930K processor (3.4 GHz), 16 GB DDR3 RAM, 4 GB NVIDIA GeForce GTX 760 video card, and Creative SB X-Fi sound card, which was connected to an EyeLink1000+ eye tracker. The stimuli were presented on 17" ViewSonic Graphics Series CRT monitors (Model G90fb) and set to a refresh rate of 85 Hz. Chinrests were used to have a fixed viewing distance of 60.33 cm from the monitors. The screen was 1024 x 768 pixels allowing for 33.67° x 25.5° of visual angle. Participants' responses were made on Cedrus model RB-834 response pads. Both eye trackers sampled eye positions 1000 times per second (1000 Hz) and their average spatial accuracy was 0.5° of visual angle with a maximum error of 1° of visual angle. Participants were calibrated using a nine-point calibration.

Stimuli

Stimuli for a rotated T among Ls search task from Peterson (2016) were used in the current study. A T target and T-like L distractors (Jiang & Chun, 2001), were presented in set sizes of four and eight on an imaginary circle with a radius of 7.8 degrees of eccentricity. Figure 4 displays the 12-possible target and distractor images: 4 clear T-like Ls with 4 rotations (0 upright, 90, 180, & 270), 4 blurred T-like Ls with the same 4 rotations as the clear ones, 2 clear

Ts rotated 90° clockwise and counter clockwise from the upright position, and 2 blurred Ts with the same rotations as the clear ones. The clear letters were 44 x 44 pixels (1.49° of visual angle) for both the vertical and horizontal lines. Both lines had a width of 4 pixels (0.13° of visual angle). The blurred T and T-like L images were created in MATLAB 2014b, with image processing toolbox (ver. 9.1), by using low-pass filtering to remove all spatial frequencies above 0.25 cycles per degree (cpd). All letter images and the fixation cross were then standardized in MATLAB to have the same mean and standard deviation luminance values, and the background was set to neutral gray.

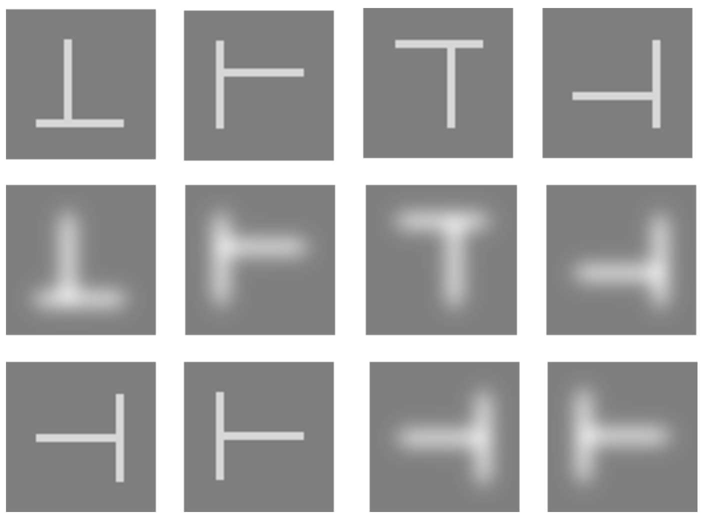

Figure 4. Images of the L and T blurred/clear letter rotations. Row 1 clear L rotated (0, 90, 180, & 270). Row 2 blurred L with same rotations. Row 3 clear T rotated (90 & 270) and blurred T rotated (90 & 270). The stimuli as shown here are likely larger than in the experiment, in which the clear stimuli measured 1.49˚ across. Thus, the blurred stimuli are likely perceived as lower frequency than was the case for the participants in the experiment.

Figure 5 shows example stimuli at both set sizes: four and eight. The set size of four letters appeared at the orientation locations of 22.5°, 112.5°, 202.5°, and 292.5°. When the set size of eight was present, letters appeared at the orientation locations of 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°. Crowding should not be an issue for either set size, since the set size of four had a Bouma's ratio (center-to-center distance between two letters minus width of letters divided by the target letter's eccentricity [Strasburger, Rentschler, & Jüttner, 2011]) of 1.23, and the set size of eight had a Bouma's ratio of 0.59, which are both above Bouma's 0.50 rule of thumb for creating crowding (Bouma, 1970).

Auditory feedback was provided through speakers at the end of each trial. A correct response produced a high pitch tone being presented, while an incorrect response produced a lower pitch tone occurring. Written feedback was also provided to the participants at each breakpoint during the study, which informed them of their cumulative accuracy in the experiment. If they were above 80%, they were told "Good Job," and if below 80%, then they were told "Try Harder."

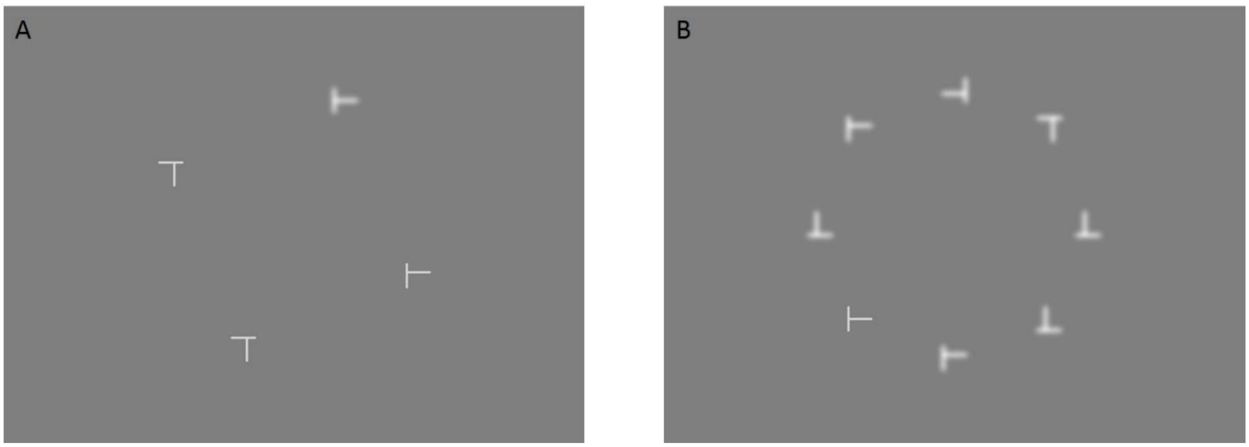

Figure 5. Set sizes of four and eight stimuli example images taken from Peterson (2016). A) Example set size of four, Blurred Target Singleton, and B) set size of eight, Clear Target Singleton example.

Design

The rotated L and T visual search was a within-subjects design with two set sizes (4 & 8). The set size of four was a 2 (*Resolution*: Blur vs. Clear) x 4 (*Condition*: All, Far, Mid, & Target) design. The set size of eight was a 2 (*Resolution*: Blur vs. Clear) x 6 (*Condition*: All, Far, Far-Mid, Mid, Near, & Target) design. All participants completed both set sizes as separate blocks, the order of which was counterbalanced. There were 368 total trials, and set sizes were counterbalanced such that half of the participants had their first 80 trials with the set size of four, followed by 288 trials that were for the set size of eight, or vice versa.

Resolution was made task-*ir*relevant (i.e., *non*-predictive of the target location), by counterbalancing several key variables. For the set size of four, the variables that were counterbalanced were target resolution (blur vs. clear), target orientation (left vs. right), and target location (1 of 4 locations). There are then five permutations for each T target with its three T-like L distractors. The five permutations were from the All, Target Singleton, and

Distractor Singleton conditions (2 Mid & 1 Far). Each target was oriented left or right equally often, but their occurrence was randomized within each participant's entire experiment. The rotation of all distractors was randomized for each trial. The set size of eight had the same variables counterbalanced, except there were more target locations (1 of 8 locations). This produced nine permutations for each T target and its seven T-like L distractors. The nine permutations were from the All, Target Singleton, and Distractor Singleton conditions (2 Near, 2 Mid, 2 Far-Mid, & 1 Far). Rotation of the target and the distractors was the same as in the set size of four.

Procedure

The experiment began by checking visual acuity with the Freiburg Visual Acuity and Contrast Test (FrACT) (Bach, 1996; Bach, 2007), followed by a 9-point calibration and validation check to align the eye tracker. Participants read through practice instructions informing them how to complete the task. Participants then completed 40 practice trials so that each *Resolution x Condition* were run through twice (16 set size 4 trials & 24 set size 8 trials). During the practice trials, auditory feedback was provided at the end of each trial indicating correct (high tone) or incorrect (low tone) responses. At the end of the practice, participants were told their cumulative accuracy score.

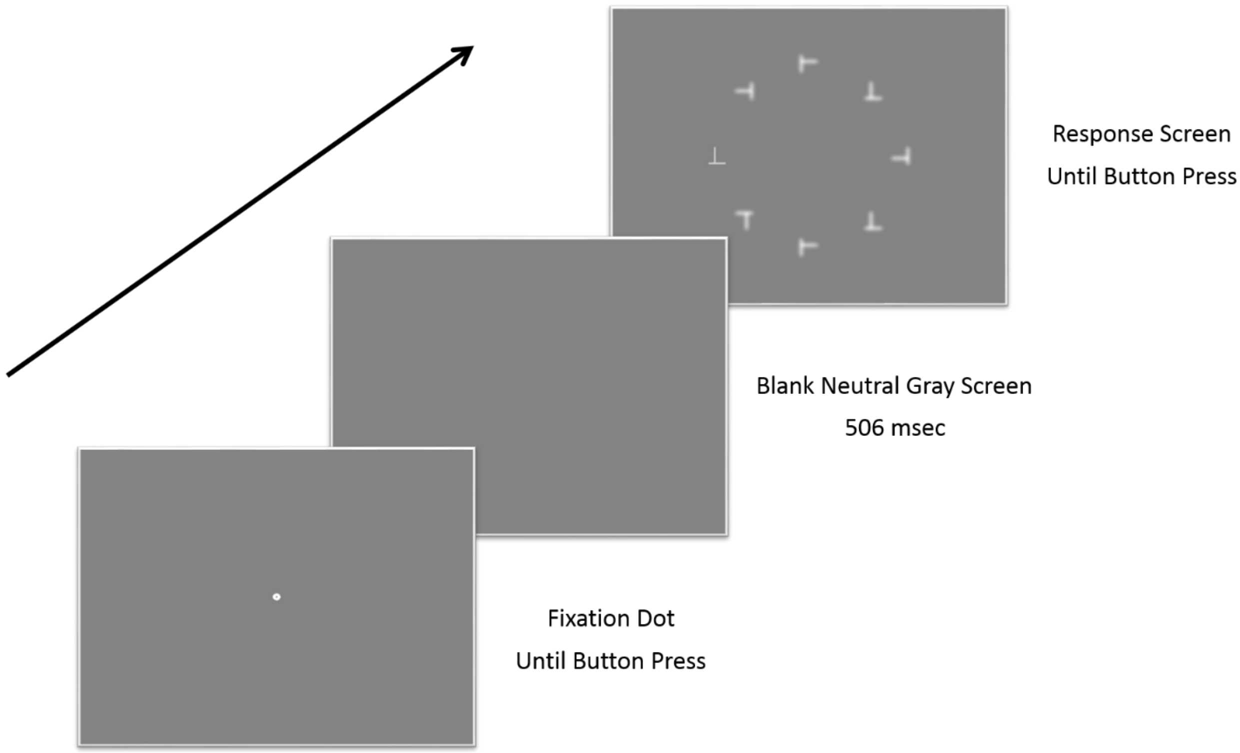

Figure 6. Experiment 1 - Trial Schematic.

Figure 6 shows the trial schematic. Participants began the trial by observing a drift correct circle at the center of the screen. Once their eyes were focused on the middle of the circle they hit the next button on the response pad. The drift correct circle was then removed from the screen and a blank neutral gray screen was presented for 506 msec followed by the presentation of the letters either at a set size of 4 or 8, which remained present until a response was made. Participants pushed the left response button to indicate they saw a T pointing left or the right response button to indicate they saw a T pointing right, then they received auditory feedback on the accuracy of their response. The auditory feedback occurred on every trial. A blank neutral gray screen was then presented for 1000 msec before the next trial started. Participants could quit or take a break at any time during the experiment. Every 92 trials the participants received a built-in break where a screen showed them their current cumulative accuracy percentage. If it was <80%, then the participants were encouraged to “Try Harder.” If their cumulative accuracy percentage was >80%, then they were told “Good Job.” After finishing the experiment, the participants were told their overall cumulative accuracy score and then read through a debriefing form and were thanked for their participation and time.

Results

Cleaning Data

The dependent variable was correct trial RT for determining the direction of the target. One participant was removed from the analyses because they had a very low accuracy score (total accuracy = 55%, next lowest 76%). Another participant was removed from analyses because they failed to complete the entire experimental session. A total of 20,414 trials were collected with a mean accuracy of 95%. The data was cleaned by removing all incorrect responses (1151 trials), and all reaction times that were < 150 msec and > 10 sec (42 trials). Therefore, a total of 1,193 trials were removed, which left 19,221 trials for the following analyses.

The reaction time analyses are all performed using Log_{10} (RT) and including Log_{10} (Trial) to normalize the distribution because the raw reaction time data had a non-normal distribution with a positive skew. The data was analyzed by the two set sizes (4 & 8). A linear multilevel model in JMP Pro 12 was used to determine whether there was a main effect for *Set Size*. The model consisted of Log_{10} (RT) predicted by *Set Size* and *Log_{10} (Trial)* as main effects. Both *Set Size* and *Log_{10} (Trial)* wo the random effects structure to vary across participants. The model had an adjusted $R^2 = .27$, RMSE = 0.20. There was a significant main effect for *Set Size*, $F(1, 54.2) = 1194.30$, $p < .001$, and *Log_{10} (Trial)*, $F(1, 53.2) = 32.37$, $p < .001$. As mentioned earlier, set size was *not* used to compare search slopes across *Resolution x Condition* cells in the design to determine if there was evidence of efficient versus inefficient search patterns. Instead, set size, as in Peterson (2016), was used in the interest of increasing the effect of resolution on selective attention. Consistent with predictions, and the results of Peterson (2016), the largest effects occurred with the set size of eight. Therefore, all following analyses were conducted split by the two set sizes, and *Log_{10} (Trial)* was included as a main effect and in the random effects structure of each linear multilevel model.

Reaction Time Analyses

Set Size 4 Reaction Time Analyses

Figure 7 shows the Log_{10} (RT) mean (M) and ± 1 standard error of the mean (SEM) from the data for *Resolution x Condition* in msec with the untransformed reaction time (RT*) as a secondary y-axis. A linear multilevel model with effect coding was performed using JMP Pro 12. The model included Log_{10} (RT) as the dependent measure, the main effects and interaction of *Resolution* and *Condition* along with the main effect of Log_{10} (Trial) were included in the fixed effects structure. The fixed effects *Resolution* and *Condition* interaction and Log_{10} (Trial) main effect were included in the random effects structure varying across participant with adjusted R^2 = .28, RMSE = 0.16. Table 2 provides the model's parameter estimates.

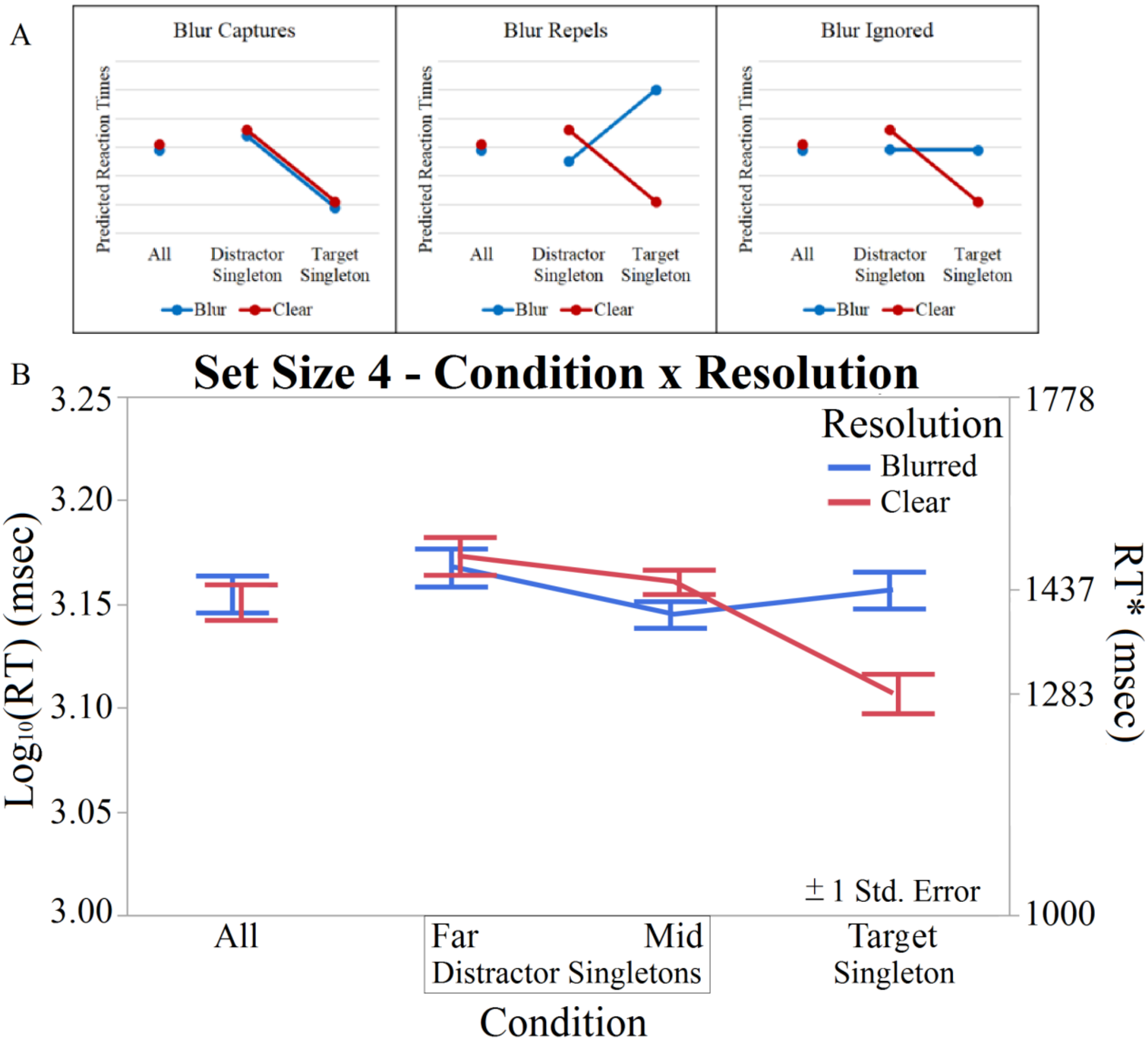

Figure 7. A) Quantitative model prediction graphs. B) The mean Log_{10} (RT) for *Condition* x *Resolution* with +/- 1 SEM bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale. The distractor conditions are boxed in to help differentiate the distractor versus target conditions.

Table 2

Parameter Estimates from the Set Size 4: Log_{10} (RT) Linear Multilevel Model

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.188	0.025	35.87	127.56	<.001
Resolution(Blurred)	0.004	0.002	68.60	1.89	0.063
Condition(All)	0.001	0.004	306.80	0.17	0.864
Condition(Far)	0.018	0.004	310.10	4.39	<.001
Condition(Mid)	0.001	0.003	98.90	0.38	0.705
Resolution(Blurred) x Condition(All)	-0.002	0.005	240.80	-0.47	0.641
Resolution(Blurred) x Condition(Far)	-0.007	0.005	241.90	-1.48	0.140
Resolution(Blurred) x Condition(Mid)	-0.011	0.004	120.70	-2.71	0.008
Log_{10} (Trial)	-0.018	0.010	26.48	-1.77	0.089

Note. Model was performed using effect coding [(Resolution: Blurred = +1, Clear = -1); (Condition: All = '+1,0,0', Far = '0,+1,0', Mid = '0,0,+1', Target = '-1,-1,-1')]. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Table 3 displays the Log_{10} (RT) *M* with within-subject *SD*, and the RT* geometric mean (*GM)* with within-subject geometric standard deviation (*GSD)* for *Resolution x Condition* in msec. Reaction times did not significantly change across the experimental trials, Log_{10} (Trial), $F(1, 26.5) = 3.12$, $p = 0.089$, indicating that the practice trials were sufficient training on the task. There was no main effect for *Resolution*, $F(1, 68.6) = 3.58$, $p = 0.063$, which suggests that the blurred and clear conditions had similar reaction times and that both resolutions were legible. There was a significant main effect for *Condition*, $F(3, 199.0) = 10.16$, $p < .001$, and an interaction for *Resolution x Condition*, $F(3, 191.5) = 6.94$, $p < .001$, which was further analyzed with a Tukey HSD test (see Table 4). As with Peterson (2016; Exp. 2), the competing alternative hypotheses must be refuted or supported based on the nature of the *Resolution x Condition* interaction.

Table 3

Set Size 4: Resolution x Condition: Log_{10} (RT) M with SD and RT GM with GSDs*

Resolution	Condition	Log_{10} (RT) M	Log_{10} (RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
Blurred	All	3.152	0.155	1421	994	2031
Blurred	Far	3.166	0.157	1465	1021	2102
Blurred	Mid	3.145	0.164	1396	958	2034
Blurred	Target	3.156	0.146	1433	1024	2004
Clear	All	3.150	0.150	1414	1002	1996
Clear	Far	3.171	0.151	1484	1047	2103
Clear	Mid	3.159	0.137	1444	1052	1981
Clear	Target	3.105	0.159	1274	884	1835

Note. RT* = Untransformed Reaction Time. M = Marginal Means. GM = Geometric Mean. SD = Within-subject Standard Deviation. GSD = Geometric within-subject Standard Deviation. RT* has asymmetrical -1 and +1 GSDs because of the positive skew of the RT data when untransformed.

Table 4

Set Size 4: Tukey HSD Comparisons - Resolution x Condition Interaction with Log_{10} (RT)

Resolution	Condition	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Clear	Far	A	3.174	0.015	3.144	3.204
Blurred	Far	AB	3.167	0.015	3.137	3.197
Clear	Mid	AB	3.161	0.014	3.133	3.189
Blurred	Target	AB	3.158	0.015	3.128	3.188
Blurred	All	AB	3.155	0.015	3.125	3.185
Clear	All	AB	3.152	0.015	3.122	3.182
Blurred	Mid	B	3.146	0.014	3.118	3.174
Clear	Target	C	3.108	0.015	3.078	3.138

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, $Q = 3.06$). Sq = Squares. Std Error = Standard Error.

As shown in Table 4 and Figure 7, and replicating Peterson (2016), the all-blurred and all-clear conditions are not significantly different, which suggests that without the presence of resolution contrast, the searches in these conditions produced random search. Furthermore, this provides confidence in the legibility of the blurred letters because the all-blurred condition RT was not significantly longer than the all-clear condition. As with Peterson (2016; Exp. 2), the all-blurred and all-clear conditions can be used as baselines to compare the influence of the singleton conditions on selective attention. As shown in Figure 7, there is strong evidence for the *Blur is Ignored* hypothesis because none of the blurred conditions significantly differed from one another, suggesting that blur is ignored by selective attention. The results provide evidence against both the *Blur Captures* hypothesis, based on the blurred target singleton having a longer RT than clear target singleton, and the *Blur Repels* hypothesis, because the blurred target singleton's RT was not significantly longer than the all-blurred condition. As predicted, the clear target singleton was responded to significantly faster than all other clear conditions, which indicates capture to unique clarity's spatial location. However, as with Peterson (2016; Exp. 2), the RT data did not reveal capture to the clear distractor singleton conditions because their responses were not significantly longer than the all-clear condition. This will be further investigated and discussed with the eye movement results. Altogether, the set size of four results supported the hypothesis that unique clarity captures attention and unique blur is ignored by selective attention.

As in Peterson (2016), model comparisons for each quantitatively predicted hypothesis were performed to find which explained the Log_{10} (RT) data best. Each model's structure included a fixed effects structure with main effects for the selected hypothesis and Log_{10} (Trial), which were both also included in the random effects structure across participants. The BIC values for all three models strongly supported the *Blur is Ignored* model (BIC = -3471.2), which was 7.7 points lower than the *Blur Repels* (BIC = -3463.5), and 27.1 points lower than the *Blur Captures* (BIC = -3444.1) models. Table 5 shows the parameter estimates for the *Blur is Ignored* model. The likelihood ratio that the Log_{10} (RT) data was produced by the *Blur is Ignored* model is 47 and 766,814 times more likely than the *Blur Repels* and *Blur Captures* models, respectively.

Table 5

Set Size 4: Parameter Estimates Log_{10} (RT) - Blur is Ignored

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.118	0.028	53.85	110.85	<.001
Hypothesis 3 - Blur is Ignored	0.029	0.005	54.21	5.73	<.001
Log_{10} (Trial)	-0.019	0.010	26.44	-1.81	0.082

Note. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Set Size 8 Reaction Time Analyses

Figure 8 displays the Log_{10} (RT) M and ± 1 SEM from the data for *Resolution x Condition* in msec with the untransformed reaction time (RT*) as a secondary y-axis. A linear multilevel model with effect coding in JMP Pro 12 was performed, which was the same as with the set size of four data, except now with the set size of eight data. Therefore, the model had Log_{10} (RT) as the dependent measure, the fixed effects structure included the main effects and interaction of *Resolution* and *Condition*, as well as the main effect of Log_{10} (Trial), all of which were included in the random effects structure across participants with adjusted R^2 = .17, RMSE = 0.21. Table 6 provides the model's parameter estimates.

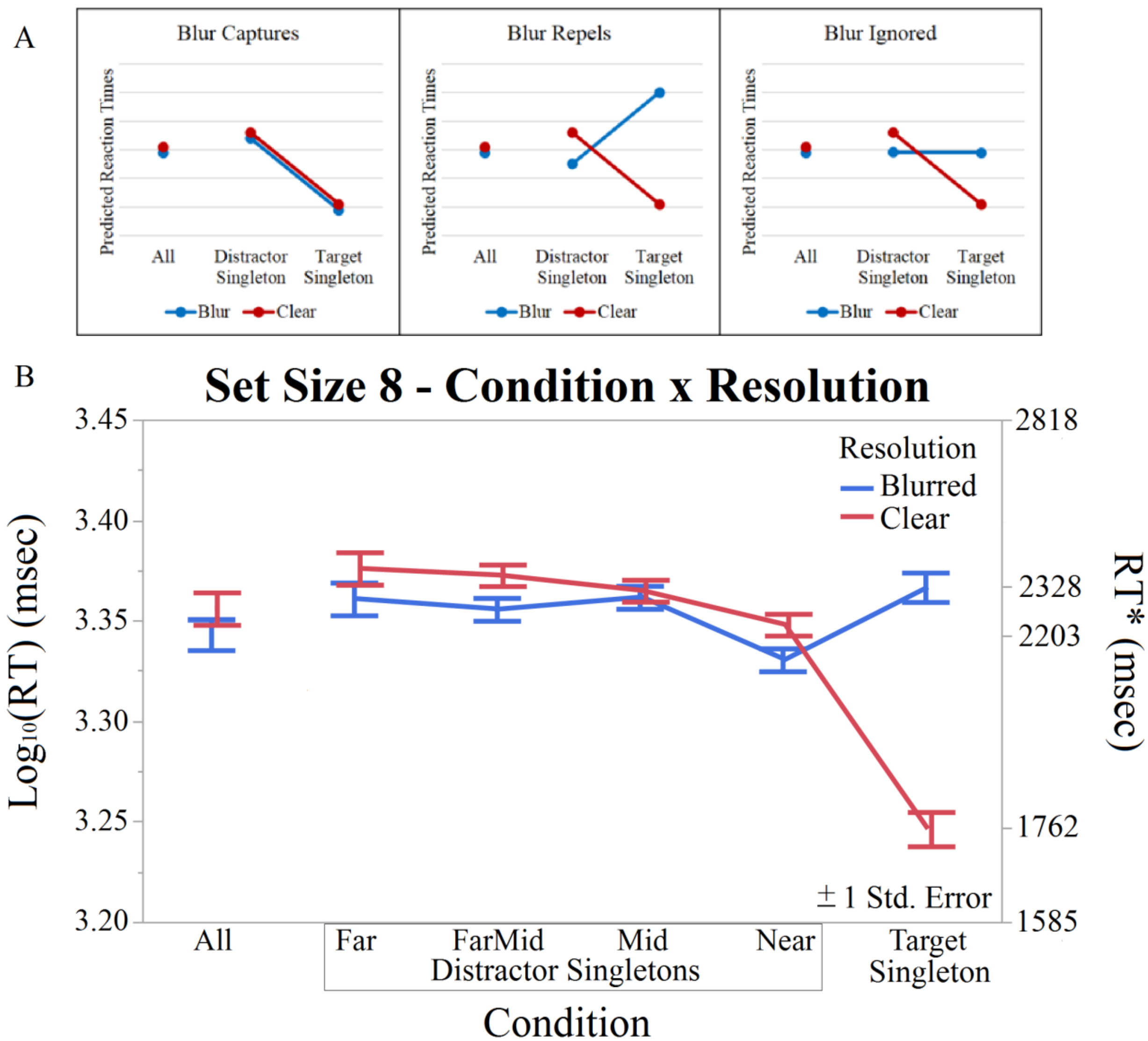

Figure 8. A) Quantitative model prediction graphs. B) The mean Log_{10} (RT) for *Condition* x *Resolution* with +/- 1 SEM bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale. The distractor conditions are boxed in to help differentiate the distractor versus target conditions.

Table 6

Parameter Estimates from the Set Size 8: Log_{10} (RT) Linear Multilevel Model

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.466	0.027	48.55	128.81	<.001
Resolution(Blurred)	0.005	0.002	62.87	2.60	0.012
Condition(All)	0.001	0.005	386.20	0.23	0.816
Condition(Far)	0.020	0.005	390.40	3.97	<.001
Condition(Far-Mid)	0.015	0.004	167.70	3.57	0.001
Condition(Mid)	0.015	0.004	167.30	3.58	<.001
Condition(Near)	-0.009	0.004	167.40	-2.20	0.029
Resolution(Blurred) x Condition(All)	-0.011	0.005	471.70	-2.26	0.024
Resolution(Blurred) x Condition(Far)	-0.012	0.005	477.40	-2.51	0.012
Resolution(Blurred) x Condition(Far-Mid)	-0.013	0.004	187.70	-3.50	0.001
Resolution(Blurred) x Condition(Mid)	-0.006	0.004	186.90	-1.68	0.095
Resolution(Blurred) x Condition(Near)	-0.013	0.004	187.20	-3.30	0.001
Log_{10} (Trial)	-0.053	0.011	32.79	-4.88	<.001

Note. Model was performed using effect coding [(Resolution: Blurred = +1, Clear = -1); (Condition: All = '+1,0,0,0,0', Far = '0,+1,0,0,0', Far-Mid = '0,0,+1,0,0', Mid = '0,0,0,+1,0', Near = '0,0,0,0,+1', Target = '-1,-1,-1,-1,-1')]. dfDen = degrees of freedom used in the denominator. Std. Error = Standard Error.

Table 7 displays the Log_{10} (RT) *M* with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for *Resolution x Condition* in msec. The results show that there was a significant main effect for Log_{10} (Trial), $F(1, 32.8) = 23.79$, $p < .001$, indicating that participants began to respond faster as they progressed through the experiment. The main effects were significant for *Resolution*, $F(1, 62.9) = 6.75$, $p = 0.012$, *Condition*, $F(5, 234.7) = 18.49$, $p < .001$, and the interaction for *Resolution x Condition*, $F(5, 269.2) = 26.79$, $p < .001$. Therefore, the interaction was further analyzed with a Tukey HSD test (see Table 8). As with the set size of 4 reaction time data and Peterson (2016; Exp. 2), the competing alternative hypotheses must be refuted/supported based on the nature of the *Resolution x Condition* interaction.

Table 7

Set Size 8: Resolution x Condition: Log_{10} (RT) M with SD and RT GM with GSDs*

Resolution	Condition	Log_{10} (RT) M	Log_{10} (RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
Blurred	All	3.343	0.204	2203	1378	3522
Blurred	Far	3.358	0.214	2282	1395	3732
Blurred	Far-Mid	3.353	0.213	2256	1380	3689
Blurred	Mid	3.361	0.220	2296	1384	3807
Blurred	Near	3.330	0.218	2139	1296	3529
Blurred	Target	3.366	0.187	2321	1511	3567
Clear	All	3.354	0.212	2261	1386	3688
Clear	Far	3.374	0.211	2365	1455	3842
Clear	Far-Mid	3.369	0.194	2340	1495	3662
Clear	Mid	3.363	0.202	2307	1449	3672
Clear	Near	3.347	0.199	2221	1403	3516
Clear	Target	3.246	0.225	1764	1049	2964

Note. RT* = Untransformed Reaction Time. M = Marginal Means. GM = Geometric Mean. SD = Within-subject Standard Deviation. GSD = Geometric within-subject Standard Deviation. RT* has -1 and +1 GSD because of the positive skew of the RT data when untransformed.

Table 8

Set Size 8: Tukey HSD Comparisons - Resolution x Condition Interaction with Log_{10} (RT)

Resolution	Condition	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Clear	Far	A	3.377	0.014	3.349	3.404
Clear	Far-Mid	A	3.372	0.013	3.347	3.398
Blurred	Target	A	3.368	0.014	3.341	3.396
Clear	Mid	A	3.365	0.013	3.340	3.391
Blurred	Mid	A	3.362	0.013	3.336	3.388
Blurred	Far	AB	3.362	0.014	3.334	3.389
Clear	All	AB	3.356	0.014	3.329	3.384
Blurred	Far-Mid	AB	3.355	0.013	3.329	3.381
Clear	Near	AB	3.348	0.013	3.322	3.374
Blurred	All	AB	3.344	0.014	3.317	3.372
Blurred	Near	B	3.332	0.013	3.307	3.358
Clear	Target	C	3.247	0.014	3.220	3.275

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, $Q = 3.30$). Sq = Squares. Std Error = Standard Error.

As displayed in Figure 8 and Table 8, the all-blurred and all-clear conditions are not significantly different, replicating the set size of four and Peterson (2016; Exp. 2). The all conditions have once again shown a lack of a legibility effect between the two resolutions and a lack of attentional guidance when there is no resolution contrast present, suggesting random search. Therefore, the all-blurred and all-clear conditions can be used again as baselines for the singleton condition to see if there is an effect on selective attention. The main findings from the set size of four were replicated and amplified with the set size of eight singleton conditions, except for the near blurred distractor condition, which was responded to faster than the blurred target condition. This supports the *Blur is Ignored* hypothesis that blur is ignored by selective attention. Interestingly, the near blurred distractor condition was responded to quickly replicating Peterson's (2016) finding, which further supports Peterson's prediction that there is some attentional capture occurring to nearby adjacent clear letters. The near blurred distractor condition may have been responded to faster than the other blur conditions because of attentional guidance towards the target. Only the near blurred distractor condition has a target at one of the adjacent positions to a blurred singleton, which may have resulted in finding the target faster.

This will be further investigated and discussed later with the eye movement results. The clear target singleton was once again responded to faster than all other conditions, suggesting that unique clarity captures attention. However, the clear distractor singleton conditions were not significantly longer than the all-clear condition. Therefore, unique clarity may be capturing attention as suggested by the fast RT for the clear target, but the RT data may not be sensitive enough to detect the attentional capture to the clear distractor singleton conditions if that is also occurring. This will be further investigated and discussed with the eye movement analyses. Overall, the findings strongly support the *Blur is Ignored* hypothesis that unique clarity captures attention and unique blur is ignored by selective attention.

As with the set size of four and Peterson (2016), model comparisons for each quantitatively predicted hypothesis were performed to find which explained the Log_{10} (RT) data best at the set size of eight. The same fixed effect and random effects structures were used to make the models for each predicted hypothesis. The BIC values for all three models, once again, strongly supported the *Blur is Ignored* model (BIC = -3725.5), which was 96.5 points lower than the *Blur Repels* (BIC = -3629.0), and 138.7 points lower than the *Blur Captures* (BIC = -3586.8) models. Table 9 shows the parameter estimates for the *Blur is Ignored* model. The likelihood ratio that the Log_{10} (RT) data was produced by the *Blur is Ignored* model is 9.0×10^{20} and 1.3×10^{30} times more likely than the *Blur Repels* and *Blur Captures* models, respectively.

Table 9

Set Size 8: Parameter Estimates Log_{10} (RT) - Blur is Ignored

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.338	0.031	75.45	108.66	<.001
Hypothesis 3 - Blur is Ignored	0.029	0.003	53.51	8.77	<.001
Log_{10} (Trial)	-0.053	0.011	32.58	-4.86	<.001

Note. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Eye Movement Analyses

All the eye movement analyses were performed using trials that had correct responses and the presence of a resolution singleton. From these trials, the letter that was first fixated on each trial was identified, which resulted in the first fixation to a singleton measure being either at the singleton or not. The analyses were conducted using R statistical software (version x64 3.3.1).

Set Size 4 First Fixation to a Singleton

Figure 9 shows the proportion of first fixations to a singleton for *Resolution x Condition*, excluding the All conditions because they both lacked the presence of a resolution singleton, since, all the letters were either blurred or presented clearly. Two multilevel logistic regressions were performed, one analysis for each resolution, in which both looked at the number of first fixations that were made to the singleton. The fixed effect structure for both regressions only included a constant and in the random effects structure the constant varied across participants. The proportion of first fixations to a singleton with 95% CIs were compared to chance (1/set size) to support or refute the competing alternative hypotheses.

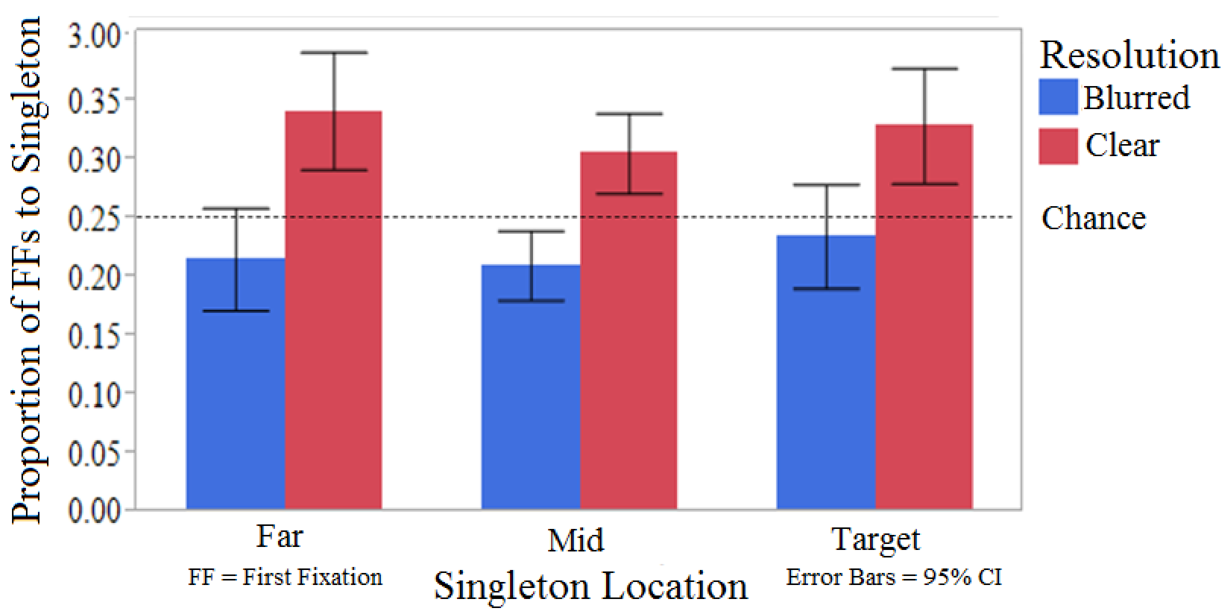

Figure 9. The mean proportion of first fixations (FFs) to the singleton for *Singleton Location x Resolution* with +/- 95% CI bars.

The clear singleton conditions' proportion of first fixations to a singleton (M = 0.312, lower 95% CI = 0.284, higher 95% CI = 0.341) was significantly higher than chance (1/set size = 0.25). This is evidence that unique clarity captures attention, not only to the clear target as shown by the RT results, but also to clear singletons that occurred at distractors. Most importantly, the blurred singleton conditions' proportion of first fixations to a singleton (M = 0.222, lower 95% CI = 0.202, higher 95% CI = 0.244) was significantly lower than chance. This is the first evidence supporting the *Blur Repels* hypothesis because the blurred singletons were looked at first at a lower than chance rate, suggesting that blur repelled attention away from its spatial location, while unique clarity captured attention to its spatial location.

Set Size 8 First Fixation to a Singleton

As with the set size of four, the set size of eight data was used to investigate the proportion of first fixations to a singleton. Figure 10 shows the proportion of first fixations to a singleton for *Resolution x Condition*, excluding the All conditions because they both lacked the presence of a resolution singleton, since, all the letters were either blurred or presented clearly. Two multilevel logistic regressions were performed to analyze the two levels of resolution separately. The fixed and random effects structures were the same as the set size of four equation structures where a constant was included as a fixed effect and varied across participants for the random effects structure. The proportion of first fixations to a singleton with 95% CIs were compared to chance (1/set size) to either support or refute the alternative competing hypotheses.

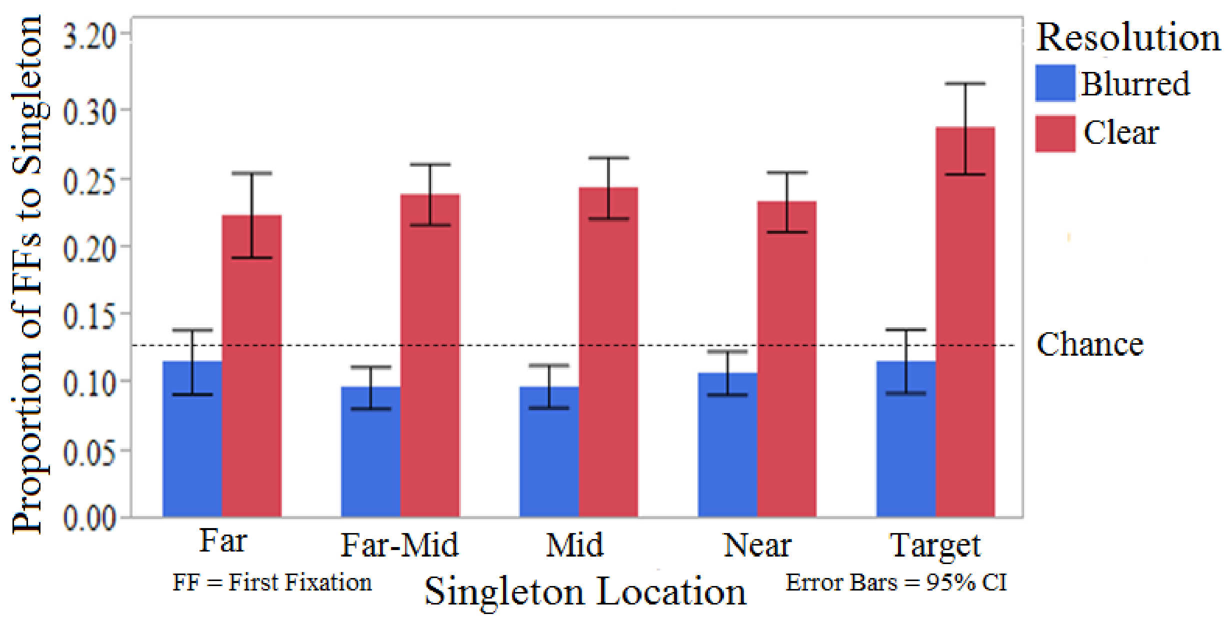

Figure 10. The mean proportion of first fixations (FFs) to the singleton for *Singleton Location x Resolution* with +/- 95% CI bars.

The set size of eight results replicated and amplified the results from the set size of four. The clear singleton conditions' proportion of first fixations to a singleton (*M* = 0.229, lower 95% CI = 0.203, higher 95% CI = 0.258) was significantly higher than chance (1/set size = 0.125). This is very strong evidence that unique clarity captures attention, not only to the clear target as shown by the RT results, but also to clear singletons that occurred at distractors. Most importantly, the blurred singleton conditions' proportion of first fixations to a singleton (*M* = 0.104, lower 95% CI = 0.095, higher 95% CI = 0.113) was significantly lower than chance. Thus, both set sizes have shown evidence supporting the *Blur Repels* hypothesis because the blurred singletons were looked at first at a lower than chance rate, suggesting that blur repelled attention away from its spatial location early on during the visual search.

First Fixated Letter Location Relative to Blurred Singleton

If unique blur is repelling attention, where is attention being guided to? Having found support for the *Blur Repels* hypothesis with the first fixation to a singleton data, two competing alternative hypotheses were developed to explain the data prior to further investigation. The *Locally Distributed* hypothesis states that unique blur repels selective attention from its spatial location towards nearby clarity. The *Equally Distributed* hypothesis states that unique blur repels from its spatial location without a spatial bias for where attention is directed. Therefore, looking at the first letter fixated for each trial during blurred singleton conditions will reveal if there was a spatial bias to where attention was directed.

As shown in Figure 11, the *Locally Distributed* hypothesis predicts that only the adjacent clear non-singleton letters should be the first letters fixated more than chance. The *Equally Distributed* hypothesis predicts that there will be an increase in first fixations to all clear letters.

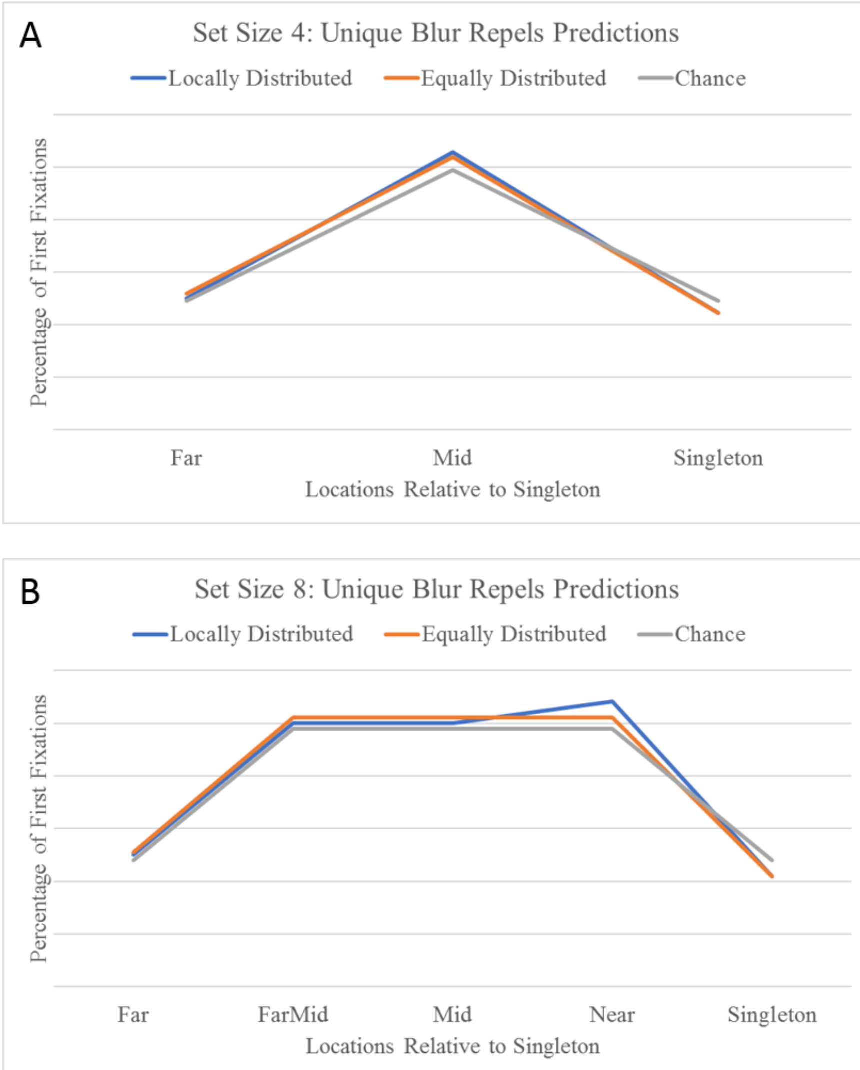

Figure 11. *Locally versus Equally Distributed* competing alternative hypotheses, A) Set size of four, B) Set size of eight. Singleton refers to blurred singletons and both hypotheses are overlapping at the singleton location on both set size graphs because that is a known value. The rest of the line is created by taking the difference between the singleton value and chance and either putting that value in addition to the near location (*Locally Distributed*) or equally across all other locations (*Equally Distributed*).

The first fixation to a blurred singleton is already known to be less than chance from both set sizes' proportion of first fixations to a singleton analyses. The following analyses investigated where those missing first fixations were located to determine if attention was being directed from unique blur to nearby clarity or was repelled away from the unique blur singleton's location without a specific direction.

Set Size 4 First Fixated Letter Location Relative to Blurred Singleton

Three multilevel logistic regressions were performed to investigate the first fixated letter's location relative to the blurred singleton. Figure 12 shows the proportion of the first fixated letter location relative to the blurred singleton for a set size of four. The three multilevel logistic regressions consisted of binomial data whether the first fixated letter was 1) the blurred singleton (1) or not (0), 2) the letter mid/adjacent to the blurred singleton (1) or not (0), or 3) the letter farthest from the blurred singleton (1) or not (0). The proportion of first fixations to each location and the 95% CIs after being converted to proportions from logit space were compared to chance.

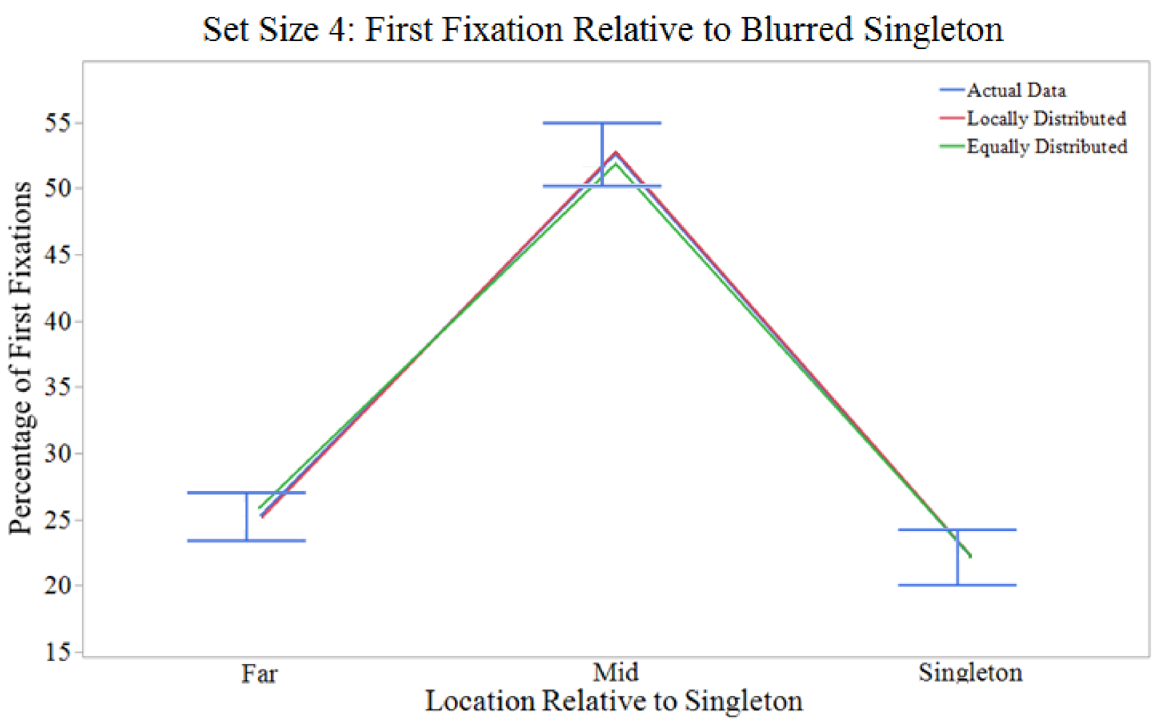

Figure 12. The mean percentage of first fixated letter's location relative to the blurred singleton for Location Relative to Singleton with 95% CI bars.

The proportion of first fixations to the blurred singleton (*M* = 0.222, lower 95% CI = 0.202, higher 95% CI = 0.244) was significantly lower than chance (1/set size = 0.25), which was already known from the set size of four first fixation to a singleton analysis. The proportion of first fixations to a letter adjacent to the blurred singleton (*M* = 0.526, lower 95% CI = 0.502, higher 95% CI = 0.550) was significantly higher than chance (chance proportion = 0.500, 2 adjacent letters to the blurred singleton with a set size of 4). This result alone is evidence supporting both the *Locally* and *Equally Distributed* hypotheses because both predict an increase in first fixation to the letters adjacent to the blurred singleton. However, the proportion of first fixations to the farthest letter from the blurred singleton (M = 0.251, lower 95% CI = 0.231, higher 95% CI = 0.273) was not significantly different from chance. Together, these results suggest that there was a spatial bias such that blur repelled attention towards nearby clarity.

Set Size 8 First Fixated Letter Location Relative to Blurred Singleton

Five multilevel logistic regressions were performed to investigate the first fixated letter's location relative to the blurred singleton. Figure 13 shows the proportion of the first fixated letter location relative to the blurred singleton for a set size of eight. Compared to the set size of four, the set size of eight required an additional two multilevel logistic regressions because the first letter fixated could have occurred at two additional locations relative to the blurred singleton. The five multilevel logistic regressions consisted of binomial data whether the first fixated letter was the location of interest (1) or not (0), 1) the blurred singleton or not, 2) the letter near/adjacent to the blurred singleton or not, 3) the letter mid distant from the blurred singleton or not, 4) the letter far-mid distant from the blurred singleton or not, or 5) the letter farthest from the blurred singleton or not. The proportion of first fixations to each location and the 95% CIs after being converted to proportions from logit space were compared to chance. With a set size of eight, the proportion of the first fixated letter to the blurred singleton or the farthest letter from the singleton was 0.125, because both have one letter location. However, the chance proportion of first fixated letter to the near/adjacent, mid, far-mid letters from the blurred singleton is 0.25, because there were two letters for each of these relative locations.

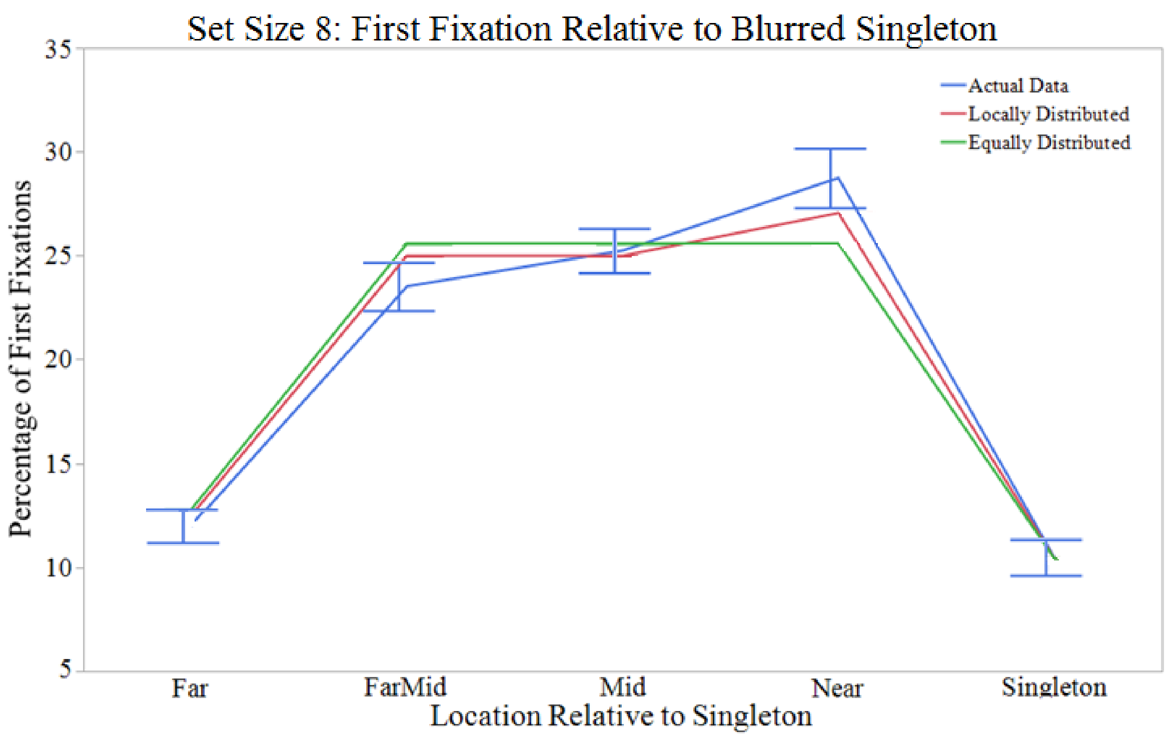

Figure 13. The mean percentage of first fixated letter's location relative to the blurred singleton for Location Relative to Singleton with 95% CI bars.

The set size of eight first fixated letter location relative to the blurred singleton replicated the findings from the set size of four and showed even stronger support for the *Locally Distributed* hypothesis. The proportion of first fixations to the blurred singleton (*M* = 0.104, lower 95% CI = 0.095, higher 95% CI = 0.113) was significantly lower than chance (1/set size = 0.125), which was already known from the set size of eight first fixation to a singleton analysis. The proportion of first fixations to a letter near/adjacent to the blurred singleton (*M* = 0.287, lower 95% CI = 0.273, higher 95% CI = 0.301) was significantly higher than chance (chance proportion = 0.25). Just as with the set size of four, this result alone is evidence supporting both the *Locally* and *Equally Distributed* hypotheses because both predict an increase in first fixations to the letters near/adjacent to the blurred singleton. However, the proportion of first fixations to the mid (*M* = 0.252, lower 95% CI = 0.241, higher 95% CI = 0.263), and far (*M* = 0.120, lower 95% CI = 0.112, higher 95% CI = 0.128), distant letters from the blurred singleton were not significantly different from chance (1/set size = 0.250 for the Mid distance [2 locations] & = 0.125 for the Far distance [1 location]). The far-mid distant letters from the blurred singleton (*M* = 0.235, lower 95% CI = 0.224, higher 95% CI = 0.247) were lower than chance. These results together support the *Locally Distributed* hypothesis because there was a spatial bias such that blur repelled attention towards nearby clarity.

Blur Repelling or Clarity Capturing?

The eye movement analyses of the first fixations relative to the blurred singleton suggested that blur repels attention towards nearby clarity. However, an alternative interpretation of the results is that a) only clarity is being selected for, and b) the clear letters adjacent to the blurred singleton are more salient than the other clear letters in the display because they are the strongest local signal of clarity. More specifically, an explanation for the First Fixations Relative to Blurred Singleton results (see Figure 13), is that a blurred singleton is treated as a degraded object and therefore ignored. An extreme version of this idea is that a blurred singleton is treated as a blank space. Obviously, this is not the case because the blurred singleton is fixated first sometimes, but it is fixated first less than chance, hence the idea that blur is treated as a degraded object and ignored. If so, then that would make a unique degree of arc between the two clear letters on either side of the blurred singleton (i.e., the ignored blurred letter would create a gap in the invisible circle created by the other clear letters, with the global configuration looking like a Landolt C). All the other clear letters would share the same degree of arc between one another on the imaginary circle. Attention could then be captured to both of the two adjacent clear letters on either side of the ignored blurred letter, which would be similar to line terminators forming a global C. Treisman and Gormican (1988) have shown line terminators to be processed preattentively based on search asymmetry evidence. Therefore, attention may be directed towards the adjacent clear letters in a similar fashion to line terminators. If the strongest local signal of clarity captures attention to the items that are line terminators that globally form a Landolt C, then that may explain the increase of first fixations seen in Figure 13 for the clear letters adjacent to the blurred singleton. But, if so, why was the blurred singleton fixated as the first item less than chance, while the clear letters not adjacent to the blurred singleton were mostly at chance?

The first fixated letter relative to the blurred singleton results showed that the adjacent clear letters were selected for early on in the trial. This may be because the strongest local signal of clarity was the adjacent clear letters to the blurred singleton, which resulted in an increase to be the first item fixated. But, the other clear letters were at or below chance. If all clarity captures attention, it would be expected that the other clear letters would also be at least slightly above chance. Instead, they were at chance or below. This result refutes that all clarity captures attention, and instead supports that either the strongest local signal of clarity captured attention or blur repelled attention toward nearby clarity.

However, if attentional capture is only to the clear letters adjacent to the blurred singleton, then a blurred singleton should be searched for at a chance level after the two adjacent clear letters have been fixated. If all clarity was capturing attention, then the blurred singleton should have been fixated last on most trials. Both predictions assume that blur is being ignored, not repelling attention. If blur is repelling attention towards nearby clarity, then the blurred singleton should have been fixated last on most trials (same prediction as *All Clarity Captures*). To investigate this further, eight multilevel logistic regressions were performed using the set size of 8 Blurred Target and All Blurred conditions to see which item number the target was fixated on during each search during a trial while including participants as a random effect. Figure 14 shows which item number the target was fixated on for the set size of 8 Blurred Target and All Blurred conditions. For example, if the target was the 6^{th} item fixated, then it was recorded as a 1, and if a distractor was fixated as the 6^{th} item or the target had been fixated at an earlier item number (1-5), then a 0 was recorded. For this analysis, items were recorded only as the first instance that they were fixated (refixated items were not recorded again). For example, if the same distractor letter was fixated twice before the target was fixated, then the distractor letter would be recorded only the first time that it was fixated. Therefore, the distractor letter would be the first item fixated and the target would be the second item fixated. Also, only the Blurred Target Singleton and All Blurred conditions in which participants fixated the target and correctly completed the task were used. When a blurred singleton was present, it is possible that participants would not need to look at the blurred singleton during the trial to correctly complete the task and thus were removed.

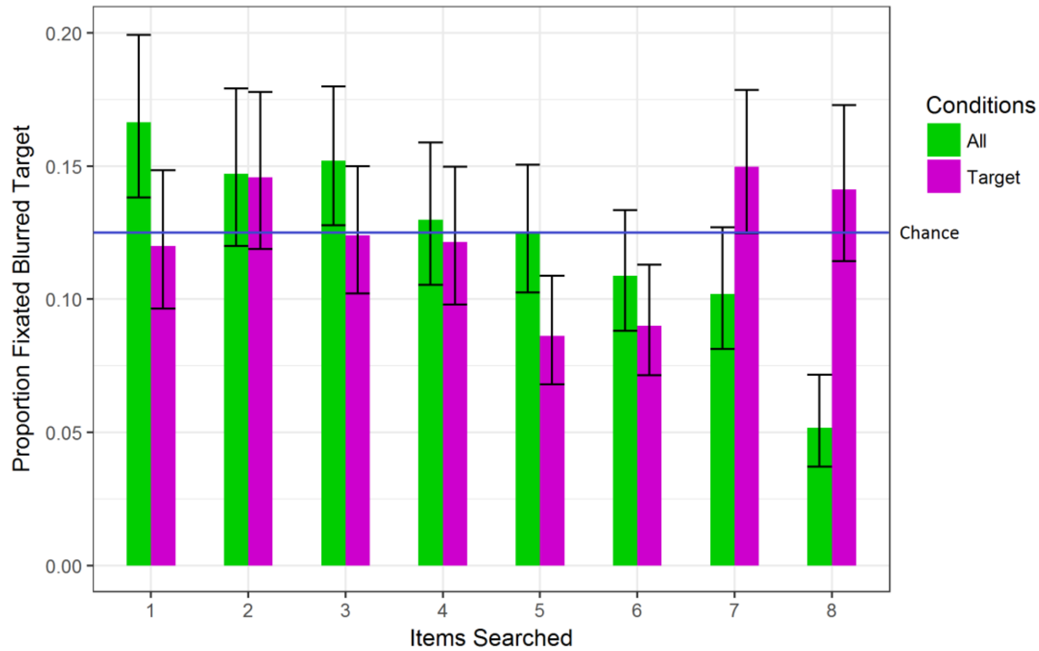

Figure 14. The proportion of trials that the blurred target was fixated as the 1st-8th item in the search for the All Blurred and Blurred Target Singleton conditions. Set size of 8 chance is 1/8 = 0.125. The error bars are 95% Confidence Intervals.

As presented in Figure 14, the All Blurred condition shows that the target is fixated first most often and then tapers off as it approaches the 8th item searched. This suggests that there was a bias to find the target earlier on in the trial than at chance (assumedly indicating that the target T can be correctly perceived to a slight degree using peripheral or parafoveal vision). Therefore, the proportion of blurred target fixated at each item number searched was compared between the Blurred Target Singleton and All Blurred conditions. The Blurred Target Singleton was fixated on the first item of the search significantly less than in the All Blurred condition, $z = 2.60$, $p = 0.009$. For items searched as the 2nd to 4th item, there was no significant difference. The Blurred Target Singleton was fixated on the fifth item of the search significantly less than in the All Blurred condition, $z = 2.43$, $p = 0.015$. There was no significant difference between the Blurred Target Singleton and All Blurred conditions at the sixth item searched. However, the seventh and eighth items searched were significantly different. The Blurred Target Singleton was fixated as the seventh item in the search significantly more than in the All Blurred condition, $z = -2.81$, $p = 0.005$, and as the eighth item, $z = -5.84$, $p < .001$. Together, these results suggest that either unique blur is repelling or all clarity is capturing attention, and provide evidence against that the clear adjacent letters to the blurred singleton are the strongest local signal of clarity that capture attention. This is because the blurred target is fixated less often first and is fixated more often as the last or second to last item in the search. While not significant, there were a fair number of trials where the blurred target was fixated as the second item in the blurred target condition. This may have been due to a clear letter adjacent to the blurred target being fixated first, then moving to the blurred target next after realizing the clear adjacent letter was not the target. However, the results overall do not support the hypothesis that a strongest local signal of clarity captured attention because the blurred singleton should have been fixated at about chance once the two clear adjacent letters had been searched. Instead, what is seen was a trend to fixate the target less and less until it increased for the 7^{th} and 8^{th} items. Therefore, the Blurred Target Fixated on Item Number searched results support that blur is repelling attention or all clarity is capturing attention, while refuting the hypothesis that a strongest local signal of clarity captured attention.

Unique blur repelled attention towards nearby clarity appears to be the best explanation of the data for now. The first fixated letter relative to the blurred singleton result supported that blur repels attention towards nearby clarity because the blurred singleton was fixated first significantly less than chance, while the clear letters adjacent to the blurred singleton were the only letters that were fixated first above chance. The blurred target singleton was also fixated last (second to last) more often in the Blurred Target Singleton condition than in the All Blurred condition. The *All Clarity Captures* hypothesis was supported by the Blurred Target Fixated on Item Number searched results but refuted by the First Fixated Letter Relative to the Blurred Singleton results. The Blurred Target Fixated on Item Number searched results provided evidence against the *Strongest Local Signal of Clarity Captures* hypothesis, but was supported by the First Fixated Letter Relative to the Blurred Singleton results.

Both *All Clarity Captures* and the *Strongest Local Signal of Clarity Captures* hypotheses are able to explain individual results quite well, but not all of the result as a larger package, whereas the *Blur Repelling Toward Nearby Clarity* hypothesis can and does. Therefore, the *Blur Repelling Toward Nearby Clarity* hypothesis explains the data better than the other two competing hypotheses.

On the other hand, perhaps by merging the hypotheses that *All Clarity Captures* and the *Strongest Local Signal of Clarity Captures* would explain the data, which is called the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis. The *Strongest Local Signal* *of Clarity, then All Other Clarity Captures* hypothesis predicts that during a blurred singleton trial, the clear letters adjacent to the blurred singleton will capture attention and be fixated first, followed by the remaining clear letters that are not adjacent to the blurred singleton, and if the target has not been found, passively fixate the blurred singleton last. Blur is assumed to be ignored by attention in this hypothesis.

One possible way to differentiate between the *Blur Repelling Towards Nearby Clarity* versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses is based on saliency models. Saliency models can be used to compare the L and T visual search displays with resolution being manipulated and predict which letter should be fixated first. Three saliency models were tested on the L and T visual search displays. Figure 15 shows the original images and the saliency maps for each of the three saliency models, which compared the Blurred Target, Clear Target, All-Blurred, and All-Clear conditions. Three salience models were selected for comparison: Graph-Based Visual Saliency ([GBVS], Harel, Koch, & Perona, 2007), Adaptive Whitening Saliency ([AWS], Garcia-Diaz, Fdez-Vidal, Pardo, & Dosil, 2012), and Weighted Maximum Phase Alignment ([WMAP], López-García, Fdez-Vidal, Pardo, & Dosil, 2011). Both the GBVS and AWS models were selected based on their strong performance from Borji, Sihite, and Itti's (2013) comparison of 35 state-of-the-art saliency models. WMAP was not compared in Borji et al. (2013), however was recommend, when gaining access to AWS, by Víctor Leborán (personal communication, March 12, 2018), who has previously worked on the AWS saliency model (Garcia-Diaz, Leborán, Fdez-Vidal, & Pardo, 2012).

GBVS has a center-bias and is able to capitalize on salient regions that are far from objects edges by using a "power-law algorithm for Markov chains" (Harel et al., 2007, p. 8). GBVS uses a typical feature filter (Itti, Koch, & Niebur, 1998; Malik & Perona, 1990) to extract featural information from images by using multiscale color, luminance intensity, and orientation maps. GBVS was selected because it was one of its strong performance from Borji et al. (2013), and its extraction of featural information includes low-pass filter, which should make this saliency model sensitive to different resolutions.

AWS was the best overall saliency model in the review by Borji et al. (2013). AWS uses multiscale color and orientation features with adaptive whitening to calculate the saliency (Garcia-Diaz, Fdez-Vidal, et al., 2012). Not only were the GBVS and AWS strong performers according to Borji et al. (2013), but both included a spatial frequency component when extracting featural information from the images. Garcia-Diaz, Leborán, et al. (2012) have shown that AWS is not biased toward specific scales. Therefore, it was thought that both saliency models would be sensitive to changes in resolution in an image. AWS has also been shown to discriminate well between search asymmetry stimuli (Garcia-Diaz, Fdez-Vidal, et al., 2012). Resolution may be a search asymmetry where unique clarity is selected for producing a more efficient search when located at the target, whereas a blurred target has been shown to be ignored (RT) or weakly repelling attention (First Fixation to Singleton results). Either way, blur's influence on attention is not capturing attention when it is non-predictive of the target's location. Such a search asymmetry would be evidence for a fixed resolution feature detector.

WMAP is similar to AWS, but one key difference is that it includes a maximum local phase alignment weight, which selects for phase alignment. According to López-García et al. (2011) when measuring the maximum local phase alignment weight:

> The importance of each visual feature is measured by maximizing in each pixel of the image and for all scales, the level of local phase alignment of the Fourier Harmonics, weighted by the strength of the visual structure in each scale… (p. 190)

The inclusion of the maximum local phase alignment weight biases the model to select for phase alignment. This may result in selecting clear objects or blurred objects because clear objects have more phase alignment than blurred objects.

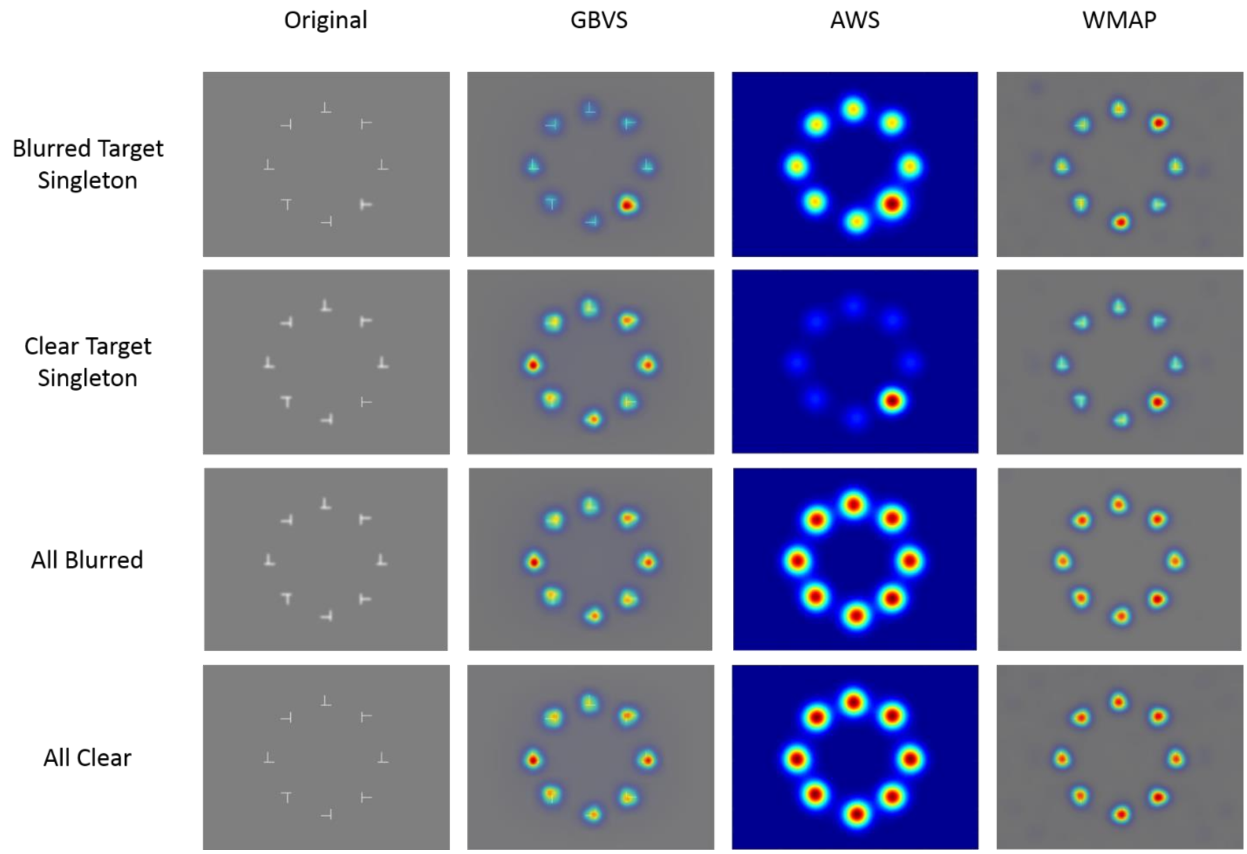

Figure 15. The original images are present in the first column where each condition has the exact same letters and orientations presented in the displays; only the resolution has changed based on the rows (Blurred Target, Clear Target, All-Blurred, & All-Clear). The saliency models' saliency maps are shown in the following columns: GBVS (2nd), AWS (3rd), and WMAP (4th). The saliency maps can be interpreted like a heat map where dark red indicates highly salient areas of the display and blue is a less salient area of the display. Each of the saliency maps have different ranges, therefore the color in each map should be thought of as relative within each map.

Based on inspecting Figure 15, the GBVS and the AWS models, which were both top saliency models in Borji et al.'s review, failed to predict the lower saliency of the blurred singletons. GBVS predicted that unique blur would be highly salient, but not unique clarity. GBVS was sensitive to resolution, but its prioritization of low resolution is completely opposite of what was found from Exp. 1's eye movement results. AWS predicted that both unique blur and unique clarity would be salient items. This is not surprising as AWS has previously been shown to not be biased toward certain scales (Garcia-Diaz, Leborán, et al., 2012). Unfortunately, for the AWS model, when resolution is task-irrelevant, the eye movement results revealed that only unique clarity is selected for, not unique blur. The WMAP model's predictions most closely fit the eye-movement data from Exp. 1. WMAP predicted that unique blur would not be selected for, while it did select for unique clarity. This is because of the maximum local phase alignment weight, which is biased towards selecting regions with phase alignment, which is found to a greater degree in the clear letters compared to the blurred letters. Interestingly, there also may be some selectivity for clear letters nearby the blurred singleton because one of the near and one of the mid clear letters on either side of the blurred target singleton were more salient than the blurred singleton and other clear letters. As expected, the All Blurred and All Clear conditions do not significantly differ from one another, which is the case for all three saliency models. Overall, the WMAP model did make predictions that fit with the Exp. 1 eye movement results. However, it is very clear that the recent best saliency models (GBVS & AWS) did not predict the eye movement results. Thus, one cannot say that *saliency models* would predict these results. At best, one can only say that some (at least one) model does predict the eye movement results, but it is not among the recent best saliency models. An even larger problem for the saliency maps it that they have not differentiated between the *Blur Repels Towards Nearby Clarity* versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses. In the best-case scenario, the blurred singleton would not be selected for, but the nearby clear letters would be most highly selected for, while the other clear letters would be somewhat selected for. The WMAP model's predictions were pretty close to the best-case scenario. It does not matter how close a saliency model can get to predicting the eye movements for the best-case scenario because the problem is that both competing hypotheses predict the best-case scenario early stated. Is the best-case scenario due to clarity capturing or blur repelling? Unfortunately, an attempt to differentiate between *Blur Repels Towards Nearby Clarity* versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses quantitatively was unsuccessful. Table 10 presents the values for the quantitative hypotheses for the *Blur Repels Towards Nearby Clarity* hypothesis versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis.

Table 10

Experiment 1 Set Size 8 Additional Competing Hypotheses' Average Number of Items Searched for Resolution x Condition

Resolution	Condition	BRTNC	SLSoCtAOCC
Blurred	All	4.5	4.5
Blurred	Far	5	5
Blurred	FarMid	5	5
Blurred	Mid	5	5
Blurred	Near	1.5	1.5
Blurred	Target	8	8
Clear	All	4.5	4.5
Clear	Far	5	5
Clear	FarMid	5	5
Clear	Mid	5	5
Clear	Near	5	5
Clear	Target	1	1

Note. BRTNC = Blur Repels Towards Nearby Clarity. SLSoCtAOCC = Strongest Local Signal of Clarity, then All Other Clarity Captures. Resolution refers to whether the singleton or all letters were presented clearly or blurred. Condition refers to the relative distance from the unique item to the target (e.g., Blurred Far is when the item farthest from the target is the only item blurred). The All conditions have no resolution contrast, all letters are either blurred or presented clearly.

The predictions produced by the two quantitative hypotheses are identical. The Blur Repels Towards Nearby Clarity hypothesis predicts that a blurred singleton will repel attention towards nearby clarity. Therefore, the first two letters that should be searched will be the two clear letters adjacent to the blurred singleton. If neither of those letters are the target, then the blurred singleton is still repelling attention, therefore search will continue by randomly searching amongst the remaining clear letters. If the target is not amongst the clear letters, then finally the blurred singleton will be searched. The *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis predicts that the two clear letters adjacent to the blurred singleton will capture attention because they are the most salient clear letters in the display because of the additional capture due to the unique degree of arc that they form, which makes them line terminators. If the target is not found amongst the clear letters adjacent to the blurred singleton, then random search will begin amongst the remaining clear letters because clarity captures attention, so all clear letters will be searched before a blurred item. Finally, if the target is not found among the clear letters, then the blurred singleton will be searched last. The predicted searches between these two hypotheses have identical search patterns, though they have different reasons for those patterns. Therefore, from Experiment 1, one cannot differentiate between the *Blur Repels Towards Nearby Clarity* versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses since the predictions for search patterns are identical and the saliency map.

Discussion

The main finding from Experiment 1 is that the *Blur Repels Towards Nearby Clarity* hypothesis versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis could not be differentiated at this point. The strongest reason for this conclusion came from quantifying the average number of items searched for each *Resolution x Condition* set for each hypothesis, which resulted in both hypotheses having identical predictions. These identical predications are also why the saliency models are unable to differentiate between the two hypotheses because both hypotheses predict identical salience maps in the best-case scenario, not just on the first item fixated, but also as the search continued beyond the first item. Unfortunately, a specific conclusion cannot be made at this point.

There is strong evidence supporting two alternative conclusions: a) blur is repelling attention towards nearby clarity, or b) clarity, especially that close to blur, captured attention from the eye movement results. The RT and quantitatively predicted hypotheses supported unique blur being ignored by attention. However, the eye movement analyses, which were more sensitive measures than RT, supported that earlier in the trial blur repelled attention towards nearby clarity (or clarity, especially that close to blur, captured attention). This is based on evidence from the first fixation to a singleton results because the blurred singletons were fixated first significantly less than chance. Upon further investigation of where attention was going, if not to the blurred singleton, the first fixated letter relative to the blurred singleton result revealed support for the *Locally Distributed* hypothesis because there was an increased proportion of first fixations at clear letters adjacent to a blurred singleton. These results also provide evidence against the *All Clarity Captures* hypothesis. The Blurred Target Fixated on Item Number searched results provided evidence against the *Strongest Local Signal of Clarity Captures* hypothesis, which showed that the blur target singleton was fixated most often as the last (or second to last) item during search. Therefore, the *All Clarity Captures* and the *Strongest Local Signal of Clarity Captures* hypotheses were merged to form the *Strongest Local Signal of*

Clarity, then All Other Clarity Captures hypothesis. The *Blur Repels Towards Nearby Clarity* hypothesis evolved from the simpler *Blur Repels* hypothesis after the *Locally Distributed* hypothesis supported the possibility that blur repelled attention towards nearby clarity. Therefore, while the two hypotheses cannot be differentiated at this point, there is strong evidence for them to explain the results.

A possible way to differentiate between *Blur Repelling Towards Nearby Clarity* versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses is to test if blur is being treated as a degraded object. An assumption of the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis is that blur is treated as a degraded object, which allows for the clear letters adjacent to the blurred singleton to form a unique degree of arc, making them locally the strongest signal of clarity, which captures attention to those two letters. The extreme version of a degraded object is an absent object. How would having a blank space influence the search pattern? It seems unlikely that a blank space would be fixated at all, so instead of having the blurred singleton fixated first ~10% of the time, a blank space may be much closer to 0%. This would allow for a much greater percentage of which item is fixated first to move around compared to only the 2.1% when a blurred singleton was present. If the clear letters adjacent to the blurred singleton were capturing attention because they had a unique degree of arc and were capturing attention in a similar fashion to line terminators (Treisman & Gormican, 1988), because the blurred singleton was treated as a degraded object, then an even greater amount of capture should be present when a blank space is between the adjacent clear letters. It is also possible that by removing the blurred singleton and leaving a blank space, all of the letters would be fixated first at an equal amount, as predicted by an All Clear condition where there is no contrast and a unique degree of arc does not capture attention to the letters forming the unique degree of arc. This potential result is possible and would be evidence that the results from Experiment 1 were due to blur repelling attention. However, if there is evidence for the strongest local signal of clarity capturing attention, it would only provide evidence that a unique degree of arc *can* result in capturing attention to the objects that create it. It would provide evidence that the Experiment 1 results may be explained by the strongest local signal of clarity, but it would not entirely rule out that when a blurred singleton is present that blur is repelling attention. Therefore, the Blank Space Experiment is a potential future experiment that could shed some light on whether blur repels and/or if the strongest local signal of clarity captures attention. However, it is an experiment focused on the attentional capture due to a unique degree of arc, whereas the focus of the current work is on the guidance of resolution on attention. Nevertheless, results from such an experiment could influence the interpretation of the current Experiment 1 results, and could be a good future direction.

However, another possible approach is through electroencephalography (EEG) by attempting to measure the distractor positivity component in an event-related potential (ERP) waveform (Gaspelin, Leonard, & Luck, 2017). Gaspelin et al. (2017) explain that based on the Sawaki and Luck (2010) signal suppression hypothesis, a distractor positivity component occurs when a salient, but task-irrelevant distractor is displayed in a scene. This salient, yet irrelevant distractor, has a bottom-up component that should capture attention to salience, but does not because of top-down suppression of the salient distractor's signal before actually capturing overt attention. While the salient, but task-irrelevant distractor does not produce oculomotor capture, the distractor positivity waveform is produced by actively suppressing a salient, but irrelevant distractor from capturing attention.

It may be possible to differentiate between the *Blur Repels Towards Nearby Clarity* versus *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses by measuring covert attention with EEG. The two hypotheses differ in their predictions of covert attention because the *Blur Repels Towards Nearby Clarity* hypothesis predicts actively repelling attention from the blurred target singleton at the start of the trial, whereas the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis predicts that blur does not actively repel attention at the start of the trial, but is ignored, and only passively fixated once all other clear letters have been fixated and the target has not been found. Therefore, when a blurred target singleton is present, if a distractor positivity waveform was detected, then that would be evidence for the *Blur Repels Towards Nearby Clarity* hypothesis, while failing to detect the distractor positivity waveform would be evidence for the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis. The RT and eye-movement measures provide behavioral and overt attention results, but the influence of blur and clarity on covert attention may reveal earlier influences of resolution on attention. For example, the interpretation from Exp. 1's results that blur may repel attention could be a simple one-step process where unique blur simply repels attention from its spatial location. However, it seems much more likely that a two-step process occurs for repulsion, in which the first step is detecting a blurred singleton, then the second step is the act of repelling attention from its spatial location toward nearby clarity. Evidence to support the hypothesis that repulsion is such a two-step process comes from Loschky et al.'s (2014) finding that blur detection was not influenced by cognitive load, which suggests that detection is a necessary first step in repulsion from blur. If repulsion from blur is a two-step process, then a letter fixated first from an attentionally capturing process (one-step process) may be more quickly fixated in a trial than a letter fixated first by an attentionally repelling process (two-step process). If repulsion from blur occurred, then the best example from Exp. 1 would be when a *non-singleton clear letter adjacent to a blurred singleton* was fixated first, and the best example of attentional capture would be when a *clear singleton* was fixated first. The time to fixate a *non-singleton clear letter adjacent to a blurred singleton* (825 msec) as the first item in the search was not longer, but actually slightly, though not significantly, shorter than a *clear singleton* (837 msec) having been fixated as the first item in the search, $t(54) = -1.52$, $p = 0.135$. This is evidence against the two-step process for repulsion from unique blur because the time to fixate a *non-singleton clear letter adjacent to a blurred singleton* (repulsion from blur) was not a slower process than fixating a *clear singleton* (capture from unique clarity). However, further research to test a one- versus two-step process of repulsion from blur would be useful.

An interesting side note is that the distractor positivity waveform is a measure of attentional suppression (Sawaki & Luck, 2010). Unique blur, when task-irrelevant, is argued to not only be suppressed, but to repel attention, which is slightly different from suppression. A stimulus that is suppressed does not have oculomotor capture (Gaspelin et al., 2017). Whereas, repelling also does not have oculomotor capture to the singleton being repelled, but does predict oculomotor capture to nearby items of the opposite side of a featural dimension. One very possible conclusion from Exp. 1's results is that blur is *repelling* attention towards nearby clarity. Therefore, it is possible that a distractor positivity waveform from attentional suppression will not be recorded if another attentional mechanism is responsible for repulsion.

Another argument to be made about why unique blur may repel attention, instead of simply being suppressed, is that blur can be visual discomforting (Juricevic, Land, Wilkins, & Webster, 2010; O'Hare & Hibbard, 2013). It may not be enough to simply not attend to the specific spatial location of unique blur when it is task-irrelevant, but to also actively direct attention away from unique blur's spatial location. The first letter fixated relative to a blurred singleton data had two competing alternative hypotheses: *Locally* and *Equally Distributed* hypotheses. Blur repelling attention essentially predicts the *Locally Distributed* hypothesis, while suppression predicts the *Equally Distributed* hypotheses because attention should not be directed toward any one clear letter, only that the blurred singleton is not fixated. Experiments 1 and 2 (*No Instructions* Task-Relevant Type) supported the *Locally Distributed* hypothesis, which further supported that blur repelled attention towards nearby clarity, instead of only being suppressed.

In the current absence of such proposed experiments, there is still good reason to think that blur repelled attention toward nearby clarity based on what is known about visual discomfort, visual accommodation, neural suppression and/or inhibitory processes. Blur has been shown to be visually discomforting (Juricevic, Land, Wilkins, & Webster, 2010; O'Hare & Hibbard, 2013). The purpose of visual accommodation is to eliminate blur and make objects of interest clearer in the fovea. Thus, blur has been shown to be visually discomforting and the visual system attempts reduce it. Therefore, actively avoiding blur seems to be a likely response for the visual system. How does the visual system avoid attending to certain spatial locations? There is neurophysiological data from Mirpour, Arcizet, Ong, and Bisley (2009) that items previously fixated during visual search produced decreased activity for that item in the lateral intraparietal area. This decrease in activity resulted in fixating new items during search, instead of refixating the same item(s). They claim that this decrease in activity acts very much like inhibition of return in saliency models (Itti et al., 1998). Itti, Koch, and Neibur (1998) included inhibition of return in their saliency model, so that the model would predict the next most salient location and not be locked to the location that was previously found to be the most salient. Adeli, Vitu, and Zelinsky's (2017) recent computational model MASC, a model of attention in the superior colliculus, uses inhibitory tagging of fixation locations and creates an inhibitory map, which then subtracts activity from a new priority map before the next fixation location is selected. The concept of inhibitory tagging and inhibition of return are not new ideas (Itti & Koch, 2001; Itti et al., 1998). However, what is a novel idea from the current dissertation, is that unique blur could be inhibited or suppressed when task-irrelevant. In addition to blur repelling attention, there needs to be one additional step of not only suppressing the blurred spatial location, but of the saliency mechanism then increasing activity to the nearby clarity. This would result in unique blur being fixated less often, and nearby clarity fixated more often.

Interestingly, Mirpour et al. (2009) also found that cell populations in the lateral intraparietal area responded with more activity to task-relevant stimuli than task-irrelevant stimuli. This is of particular interest, as this change in neural activity comes from top-down processes rather than bottom-up processes. To relate this finding to the current study, when resolution is task-irrelevant, clarity may be assumed by the visual system to be task-relevant and blur task-irrelevant. It is possible that clarity is learned to be the more informative feature because the goal of accommodation is to make objects that we want to identify clear. Thus, this could result in a continuously reinforcing reward for fixating clarity rather than blur. Therefore, the lateral intraparietal area could have greater activity to unique clear items, and reduced activity for unique blurred items, which would result in the selection of clear items over blurred items. In sum, the hypothesis that blur repels towards nearby clarity is a theoretically plausible conclusion.

The current research has focused on understanding how resolution guides attention, and has found evidence that when resolution was task-irrelevant unique clarity captured attention, while unique blur repelled attention towards nearby clarity (or clarity, especially that close to blur, captured attention). Participants were not instructed to use blur or clarity during the experiment and resolution was non-predictive of the target locations, thus using one resolution over the other would not aid in finding the target. Yet, the results do indicate an asymmetry, where clarity captures and blur appears to repel attention. Is resolution a search asymmetry? Experiments 2 and 3 investigate this research question and if blur and clarity are processed preattentively.

Chapter 3 - Experiments 2 & 3: Resolution x Task-Relevance: Resolution is Not a True Search Asymmetry and is Processed Preattentively

The aim of Experiment 2 is to provide evidence whether resolution is a search asymmetry. The reaction time results from Exp. 1 and Peterson (2016), revealed a search asymmetry where unique clarity can be used to guide attention, while unique blur does not. The eye movement results from Exp. 1 suggested that blur may weakly repel attention towards nearby clarity or that all clarity captures attention with heightened selectivity to clarity that borders blur. Both findings are evidence of a fixed resolution feature detector, which is selective for clarity. Similar to Treisman and Souther's (1985) Q amongst Os search asymmetry, searching for the presence of the critical feature (the line in the O making a Q), produced an efficient search, while searching for the lack of a critical feature (no line in an O amongst Qs), produced an inefficient search. In Experiment 1 and in Peterson (2016), resolution has two levels, blur and clarity. Clarity has the full range of spatial frequency information, while blur lacks higher spatial frequency information. Therefore, searching for a unique blurred letter may be like searching for the lack of a critical feature, whereas searching for a unique clear letter may be like searching for the presence of a critical feature. However, to determine if resolution is a search asymmetry, resolution needs to be made task-relevant. Specifically, Treisman and Souther showed that searching for an O amongst Qs was an inefficient search when the O was the target, thus making it task-relevant. Resolution in Exp. 1 and in Peterson (2016) was not task-relevant because it was not predictive of the target location. The task was to either determine if the T was present (Peterson, 2016; Exp. 1), or if the T was pointed to the left or the right (Current Exp 1.; Peterson, 2016; Exp. 2). The task was never to find the blurred or clear T; thus, resolution was not part of the task.

By making resolution task-relevant, we can determine whether resolution is a search asymmetry. If resolution is a search asymmetry, then the RT and eye movement findings from Exp. 1 should be replicated. Theoretically, this would suggest the existence of a fixed resolution feature detector, which is selective for clarity. However, if resolution is not a search asymmetry, instead the influence of resolution on attention is contingent upon its task-relevance, then unique blur should be selected for by attention. Theoretically, this would suggest the existence of a reconfigurable resolution feature detector, which can be selective for different regions (blur & clarity) on the resolution spectrum.

Experiment 3 extends the investigation into whether resolution is a search asymmetry and furthermore whether blur and clarity are both processed preattentively. Experiment 3 uses a feature search to have participants specifically detect a blurred or clear target while manipulating set size, which allows for RT x Set Size slopes to be compared. The RT x Set Size slopes in feature searches have been used as evidence for preattentive or attentional processing (Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989) and where contrast between feature pairs are a search asymmetry (Treisman & Gormican, 1988; Treisman & Souther, 1985).

Experiment 2: Resolution x Task-Relevance: Resolution is Not a True Search Asymmetry

The aim of Experiment 2 was to determine whether resolution is a search asymmetry, and thereby suggesting either the existence of a fixed or reconfigurable resolution feature detector. The reaction time results from Peterson (2016) are potentially explained by visual resolution being a search asymmetry, which suggested a fixed resolution feature detector. However, Enns and MacDonald's (2013) Experiment 4 results can be taken to suggest that resolution is not a search asymmetry because unique blur was searched for when it became task-relevant. Thus, visual resolution may not be a search asymmetry, but instead resolution's influence on selective attention may be contingent upon its task-relevance, which would suggest a reconfigurable resolution feature detector. To investigate whether visual resolution is a search asymmetry, making resolution task-relevant will allow for evidence to support or refute the two competing alternative hypotheses (Table 11).

Table 11

Visual Resolution Search Asymmetry Competing Hypotheses for RT and First Fixation to a Singleton

	Visual Resolution is a Search Asymmetry			
	Clarity Task-Relevant	Clarity Task-Irrelevant	Blur Task-Relevant	Blur Task-Irrelevant
RT Predictions	Clear Target < All-clear	Clear Target < All-clear	**Blurred Target ≥ All-Blurred**	Blurred Target ≥ All-Blurred
First Fixation to a Singleton Predictions	Clear Singleton > Chance	Clear Singleton > Chance	**Blurred Singleton ≤ Chance**	Blurred Singleton ≤ Chance

	Visual Resolution's Influence on Attention is Contingent on Task-Relevance			
	Clarity Task-Relevant	Clarity Task-Irrelevant	Blur Task-Relevant	Blur Task-Irrelevant
RT Predictions	Clear Target < All-clear	Clear Target < All-clear	**Blurred Target < All-blurred**	Blurred Target ≥ All-Blurred
First Fixation to a Singleton Predictions	Clear Singleton > Chance	Clear Singleton > Chance	**Blurred Singleton > Chance**	Blurred Singleton ≤ Chance

Note. All the RT and First Fixation to a Singleton predictions are the same between the two competing hypotheses, except for when blur is task-relevant. According to the *Visual Resolution is a Search Asymmetry* hypothesis, when blur is task-relevant, it will not be selected for. According to the *Visual Resolution's Influence on Attention is Contingent on Task-Relevance* hypothesis, when blur is task-relevant it will be selected for. The First Fixation to a Singleton predictions are compared to chance as equal to 1/set size.

Method

Participants

There were 96 participants from Kansas State University's Psychological Sciences undergraduate research pool (61 females, mean age = 19.93). Participants' vision was tested to be 20/30 or better. All participants were naïve to the purpose of the experiment and were not participants in Experiment 1. Study procedures were approved by Kansas State University's Institutional Review Board, and all participants gave their informed consent prior to completing the study, which they received class credit for.

Apparatus and Stimuli

All the stimuli were the same as in Experiment 1, except for the following changes. As shown in Figure 16, a set size of 6 was used, instead of set sizes 4 and 8. The same basic result patterns emerged from the set sizes of 4 and 8 in Exp. 1. However, there were larger effects for the set size of 8 than 4. By using a set size of 6 a compromise was made between the larger effects from the set size of 8, which required more trials and the smaller, though consistent, effects from the set size of 4, which required less trials. The set size of 6 was expected to produce medium effects relative to the set size of 4 and 8 previous result patterns and reduce the number of trials needed by only having one set size, which was less than the set size of 8. As in Experiment 1, letters were presented on an imaginary circle with a radius of 7.8 degrees of visual angle. Letters appeared from the top of the imaginary circle at the orientation locations of 0˚, 60˚, 120˚, 180˚, 240˚, and 300˚. A central drift correct circle appeared at the start of the trials and was replaced by a 3 x 3 pixels white square (0.1˚ of visual angle) at the center of the screen, which remained present when the letter stimuli appeared.

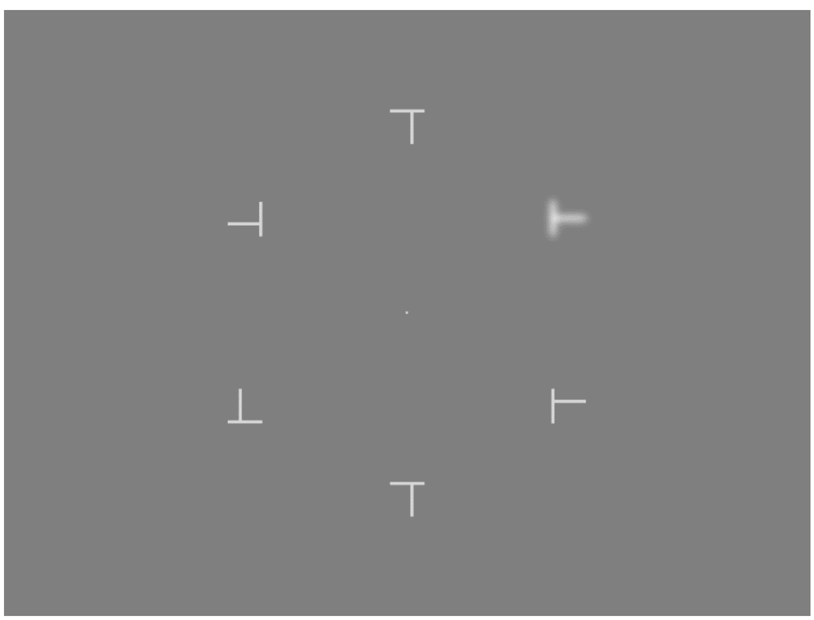

Figure 16. Set size of six Blurred Target Singleton example.

Design

A mixed design was used such that *Task-Relevance Type* (*Use Blur*, *Use Clarity*, *Do Not Use Unique Blur or Clarity*, and *No Instructions*) was a between-subjects variable, while *Resolution* (Blur & Clarity) and *Condition* (All, Far, Mid, Near, & Target) were within-subjects variables. However, the number of trials for each *Resolution x Condition* set was dependent on *Task-Relevance*.

The *Task-Relevance Types* were produced by both instructions and probability manipulations of the *Resolution x Condition* set trials. The instructions were very explicit with the participants about the usefulness of resolution to find the target during the experiment, to hopefully get the effect immediately in the experiment. The probability manipulations were used so that the instructions were truthful (without the probability manipulation, there would have been deception, which the participants would realize over time, and they would likely then ignore the instructions).

Instruction Manipulation

Instructions were provided at the beginning of the experiment and during each mandatory break point during the experiment (Table 12).

Table 12

Instructions for Each Task-Relevance Type

Task-Relevance Type	Instructions
Use Blur	"If you see a uniquely blurred letter, it will most often be the target. Looking for unique blur will help you find the target."
Use Clarity	"If you see a uniquely clear letter, it will most often be the target. Looking for unique clarity will help you find the target."
Do Not Use Unique Blur or Clarity	"If you see a uniquely blurred or clear letter, it will most often NOT be the target. Looking for unique blur or clarity will not help you find the target."
No Instructions	[Participants only received basic instructions about completing the orientation of the T target task without instructions related to resolution.]

Note: Instructions for all task-relevance types.

Probability Manipulation

The frequency of trials is shown for the *Do Not Use Unique Blur or Clarity* and the *No Instructions* task-relevance types in Table 13, the *Use Blur* task-relevance type in Table 14, and the *Use Clarity* task-relevance type in Table 15. The *No Instructions* and the *Do Not Use Unique Blur or Clarity* task-relevance types both had resolution non-predictive of the target location just like in Exp. 1, but with a set size of six. The following variables were counterbalanced: target resolution (blur vs. clear), target orientation (left vs. right), and target location (1 of 6 locations). There are seven permutations for each T target and five T-like L distractors. The seven permutations are from the All, Target Singleton, and Distractor Singleton conditions (2 Near, 2 Mid, 1 Far). The *Task-Relevance Types*, *Use Blur* and *Use Clarity*, had both their *Resolution x Condition* trials manipulated such that within the resolution of interest, when the unique singleton was present, it occurred at the target location on 2/3 of trials. The other resolution was non-predictive of the target location by having the unique singleton appear at the target location on 1/6 of trials. The probability manipulation was selected based on several considerations: counterbalancing, total number of trials, and iteration counts of specific conditions within each experimental session.

Table 13

Experimental Trial Frequencies for Do Not Use Unique Blur or Clarity and No Instructions Types

	Target	Near	Mid	Far	All	Total
Blur	20	40	40	20	40	160
Clear	20	40	40	20	40	160
Total	40	80	80	40	80	320

Note. Do Not Use Unique Blur or Clarity and *No Instructions* have resolution non-predictive of the target location. Number of trials for each *Resolution x Condition*.

Table 14

Experimental Trial Frequencies for Use Blur Type

	Target	Near	Mid	Far	All	Total
Blur	80	16	16	8	40	160
Clear	20	40	40	20	40	160
Total	100	56	56	28	80	320

Note. Use Blur has unique blur occur at the target on 2/3 of trials, unique clarity is non-predictive of the target location occurring at the target on 1/6 of trials. Number of trials for each *Resolution x Condition*.

Table 15

Experimental Trial Frequencies for Use Clarity Type

	Target	Near	Mid	Far	All	Total
Blur	20	40	40	20	40	160
Clear	80	16	16	8	40	160
Total	100	56	56	28	80	320

Note. Use Clarity has unique clarity occur at the target on 2/3 of trials, unique blur is non-predictive of the target location occurring at the target on 1/6 of trials. Number of trials for each *Resolution x Condition*.

As with Exp. 1, each target was oriented left or right equally, but their occurrence was randomized within each participant's entire experiment. The rotation of all distractors was randomized for each trial. RT and eye movements were recorded as the dependent variables. Accuracy was also recorded but was only used as a control variable for cleaning the data.

Procedure

The experimental procedure was the same as in Exp. 1, except for the following changes. Practice trials matched the *Task-Relevance Type* the participants were in and they received 80 practice trials but reduced the number of trials for each *Resolution x Condition* set to be 1/4th of the experimental *Resolution x Condition* set.

After the practice trials, the experimental trials started. As shown in Figure 17, the only difference from Experiment 1 was that following the drift correct screen that initiated the trial, a small light gray dot appeared at the center of the screen and remained present until the end of the trial. This was included to keep participants looking at the center of the screen before the letters were presented.

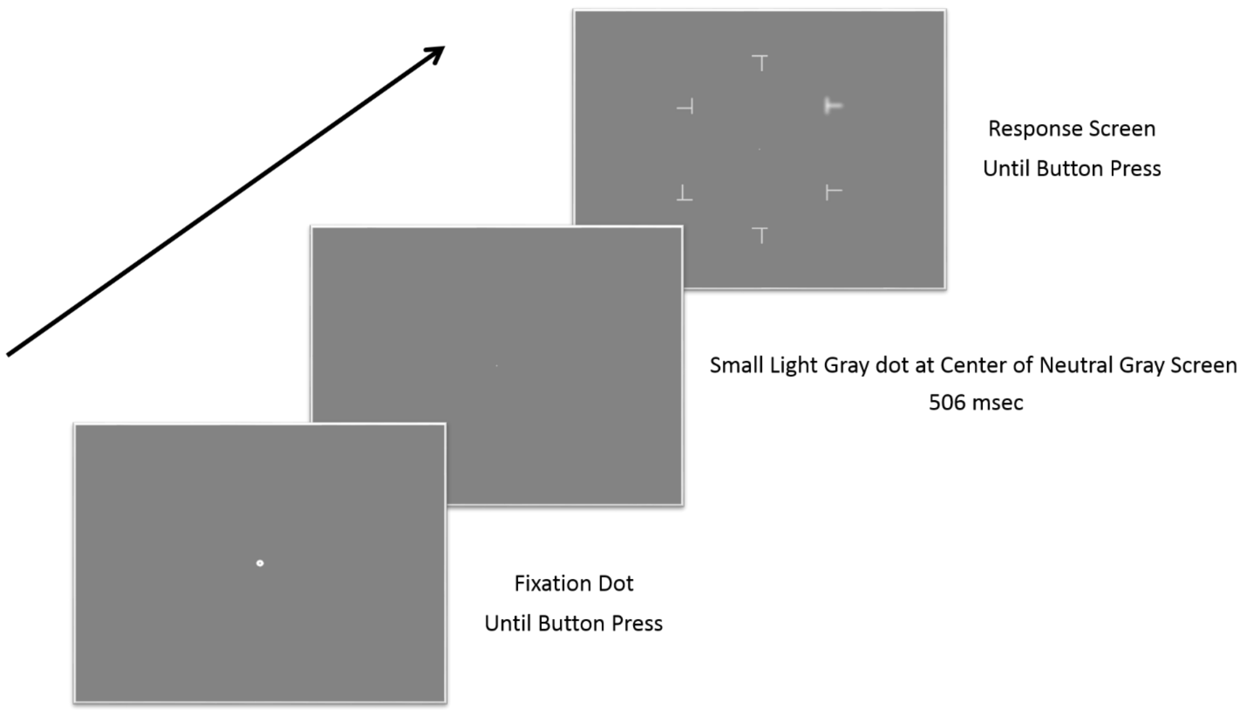

Figure 17. Experiment 2 - Trial Schematic.

Mandatory breaks occurred after every 80 trials and there was a total of 320 trials. Feedback was provided during the breaks just as in Exp. 1, but before they would begin the next set of trials, participants received instructions again about resolution's task-relevance.

Results

Cleaning Data

A total of 30480 trials were collected with a mean accuracy of 96%. The data was cleaned by removing all incorrect responses (1284 trials), and all reaction times that were < 150 msec and > 10 seconds (6 trials). Therefore, a total of 1,290 trials were removed, which left 29,190 trials for the following analyses.

Reaction Time Analyses

As with the Experiment 1 RT analyses, the following analyses were completed using the dependent measure of correct trial reaction times to determine the direction of the target. The following analyses were all performed using Log_{10} (RT) to account for the non-normal distribution of the raw reaction time data. Figure 18 shows the mean Log_{10} (RT) and ± 1 SEM for *Resolution x Condition* in msec with the untransformed reaction time (RT*) as a secondary y-axis. A linear multilevel model with effect coding was performed in JMP Pro 12. The model included Log_{10} (RT) as the dependent measure, *Task-Relevance Type, Resolution,* and *Condition* were included as three main effects, three two-way interactions, and one three-way interaction, and *Log_{10} (Trial)*, which was centered, was included as a main effect. The categorical variable were effect coded: [(Task-Relevance Type: *Do Not Use Unique Blur or Clarity* = '+1,0,0', *No Instructions* = '0,+1,0', *Use Blur* = '0,0,+1', *Use Clarity* = '-1,-1,-1'); (Resolution: Blurred = +1, Clear = -1); (Condition: All = '+1,0,0,0', Far = '0,+1,0,0', Mid = '0,0,+1,0', Near = '0,0,0,+1', Target = '-1,-1,-1,-1')]. The random effects structure included the main effects and interaction for *Resolution x Condition* and the main effect of *Log_{10} (Trial)* across participants with adjusted R^2 = .28, RMSE = 0.18. Table 16 provides the model's parameter estimates.

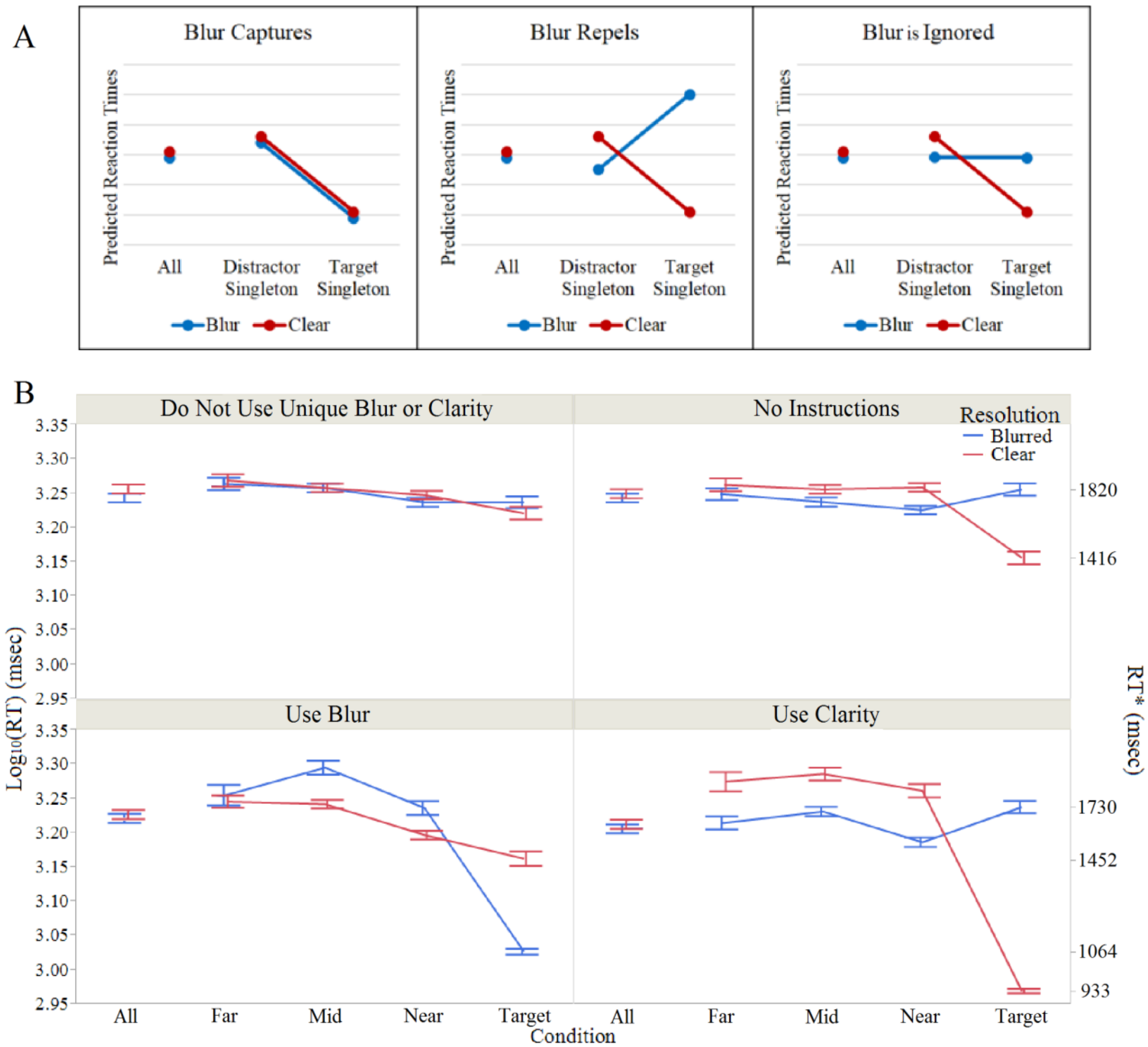

Figure 18. A) Quantitative model prediction graphs. B) The mean Log_{10} (RT) for *Task-Relevance Type x Condition* x *Resolution* with +/- 1 SEM bars. Secondary y-axis presents untransformed reaction time (RT*) values in msec distributed on a logarithmic scale. The blurred target and clear target RT* values are presented for all task-relevance types, except for *Do Not Use Unique Blur or Clarity* (Blurred target M = 1722 msec & Clear Target M = 1656 msec).

Table 16

Parameter Estimates for Log_{10} (RT) Task-Relevance Type x Condition x *Resolution Linear Multilevel Model*

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.289	0.013	143.40	245.29	<.001
TRT(DNUUBoC)	0.022	0.011	92.39	2.06	0.042
TRT(NI)	0.011	0.011	92.99	1.00	0.319

TRT(UB)	-0.015	0.011	93.51	-1.37	0.175
Res(Blurred)	0.001	0.001	119.30	0.89	0.373
Cond(All)	0.005	0.003	309.40	1.93	0.055
Cond(Far)	0.027	0.003	820.00	7.76	<.001
Cond(Mid)	0.031	0.003	403.70	10.73	<.001
Cond(Near)	0.005	0.003	401.80	1.69	0.093
TRT(DNUUBoC)*Res(Blurred)	-0.002	0.002	100.80	-1.14	0.259
TRT(NI)*Res(Blurred)	0.001	0.002	99.50	0.73	0.470
TRT(UB)*Res(Blurred)	-0.006	0.002	138.40	-2.44	0.016
TRT(DNUUBoC)*Cond(All)	-0.005	0.005	300.60	-1.07	0.286
TRT(DNUUBoC)*Cond(Far)	-0.010	0.006	638.50	-1.86	0.063
TRT(DNUUBoC)*Cond(Mid)	-0.022	0.005	331.30	-4.55	<.001
TRT(DNUUBoC)*Cond(Near)	-0.011	0.005	329.40	-2.38	0.018
TRT(NI)*Cond(All)	0.001	0.005	299.00	0.29	0.774
TRT(NI)*Cond(Far)	-0.011	0.006	635.40	-1.94	0.053
TRT(NI)*Cond(Mid)	-0.024	0.005	330.50	-4.96	<.001
TRT(NI)*Cond(Near)	-0.001	0.005	328.60	-0.31	0.760
TRT(UB)*Cond(All)	0.008	0.005	318.50	1.62	0.107
TRT(UB)*Cond(Far)	0.012	0.006	1008.00	1.84	0.066
TRT(UB)*Cond(Mid)	0.026	0.005	478.70	4.78	<.001
TRT(UB)*Cond(Near)	0.002	0.005	473.50	0.32	0.752
Res(Blurred)*Cond(All)	-0.005	0.003	278.60	-1.90	0.058
Res(Blurred)*Cond(Far)	-0.011	0.003	758.60	-3.14	0.002
Res(Blurred)*Cond(Mid)	-0.004	0.003	366.40	-1.28	0.203
Res(Blurred)*Cond(Near)	-0.010	0.003	364.90	-3.58	<.001
TRT(DNUUBoC)*Res(Blurred)*Cond(All)	-2.3E-04	0.005	270.60	-0.05	0.960
TRT(DNUUBoC)*Res(Blurred)*Cond(Far)	0.009	0.006	587.10	1.58	0.115
TRT(DNUUBoC)*Res(Blurred)*Cond(Mid)	0.004	0.005	298.70	0.91	0.366
TRT(DNUUBoC)*Res(Blurred)*Cond(Near)	0.008	0.005	297.50	1.68	0.093
TRT(NI)*Res(Blurred)*Cond(All)	-0.001	0.005	268.70	-0.17	0.866
TRT(NI)*Res(Blurred)*Cond(Far)	-9.8E-05	0.006	583.70	-0.02	0.986
TRT(NI)*Res(Blurred)*Cond(Mid)	-0.008	0.005	298.60	-1.72	0.087
TRT(NI)*Res(Blurred)*Cond(Near)	-0.008	0.005	296.80	-1.75	0.082
TRT(UB)*Res(Blurred)*Cond(All)	0.007	0.005	287.00	1.49	0.137
TRT(UB)*Res(Blurred)*Cond(Far)	0.018	0.006	938.00	2.78	0.006
TRT(UB)*Res(Blurred)*Cond(Mid)	0.035	0.005	436.70	6.56	<.001

TRT(UB)*Res(Blurred)*Cond(Near)	0.034	0.005	432.10	6.43	<.001
Log10 (Trial)	-0.031	0.006	93.27	-5.37	<.001

Note. Task-Relevance Type = TRT. *Do Not Use Unique Blur or Clarity* = DNUUBoC. *No Instructions* = NI. *Use Blur* = UB. *Use Clarity* = UC. Resolution = Res. Condition = Cond. Model was created using effect coding [(Task-Relevance Type: DNUUBoC = '+1,0,0', NI = '0,+1,0', UB = '0,0,+1', UC = '-1,-1,-1'); (Resolution: Blurred = +1, Clear = -1); (Condition: All = '+1,0,0,0', Far = '0,+1,0,0', Mid = '0,0,+1,0', Near = '0,0,0,+1', Target = '-1,-1,-1,-1')]. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Table 17 displays the Log_{10} (RT) *M* with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for *Task-Relevance Type x Resolution x Condition* in msec. The results show that there was a significant main effect for *Log_{10} (Trial)*, $F(1, 93.3) = 28.89$, $p < .001$, indicating that participants began to respond faster as they progressed through the experiment. The main effects were not significant for *Task-Relevance Type*, $F(3, 93.1) = 2.42$, $p = 0.071$, and *Resolution*, $F(1, 119.3) = 0.80$, $p = 0.373$, indicating that reaction time was not influenced solely on the *Task-Relevance Type* or *Resolution*. The main effect was significant for *Condition*, $F(4, 427.5) = 140.10$, $p < .001$, indicating at least one condition was faster or slower than another condition. By inspecting Figure 18, it appears very likely that the target condition is faster than one if not all the other conditions. The two-way interaction for *Task-Relevance Type x Resolution*, $F(3, 115.7) = 3.77$, $p = 0.013$, indicating that at least one *Task-Relevance Type x Resolution* set was faster or slower than one or more other *Task-Relevance Type x Resolution* set(s). The two-way interaction for *Task-Relevance Type x Condition*, $F(12, 417.3) = 18.37$, $p < .001$, indicating that at least one *Task-Relevance Type x Condition* set was faster or slower than one or more other *Task-Relevance Type x Condition* set(s). The two-way interaction for *Resolution x Condition*, $F(4, 388.1) = 25.94$, $p < .001$, indicating that at least one *Resolution x Condition* set was faster or slower than one or more other *Resolution x Condition* set(s). The three-way interaction for *Task-Relevance Type x Resolution x Condition*, $F(12, 378.3) = 49.08$, $p < .001$, indicating that at least one *Task-Relevance Type x Resolution x Condition* set was faster or slower than one or more other *Task-Relevance Type x Resolution x Condition* set(s). Therefore, the three-way interaction was further analyzed with a Tukey HSD test (see Table 18). The competing alternative hypotheses must be refuted/supported for each *Task-Relevance* Type based on the nature of the *Task-Relevance Type x Resolution x Condition* interaction.

Table 17

Task-Relevance x Resolution x Condition: Log_{10} (RT) M with SD and RT GM with GSDs*

Task-Relevance	Resolution	Condition	Log_{10} (RT) M	Log_{10} (RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
DNUUBoC	Blurred	All	3.242	0.186	1746	1138	2679
DNUUBoC	Blurred	Far	3.263	0.190	1832	1183	2838
DNUUBoC	Blurred	Mid	3.257	0.187	1807	1175	2780
DNUUBoC	Blurred	Near	3.238	0.190	1730	1117	2679
DNUUBoC	Blurred	Target	3.236	0.161	1722	1189	2495
DNUUBoC	Clear	All	3.255	0.185	1799	1175	2754
DNUUBoC	Clear	Far	3.268	0.187	1854	1205	2851
DNUUBoC	Clear	Mid	3.258	0.176	1811	1208	2716
DNUUBoC	Clear	Near	3.246	0.175	1762	1178	2636
DNUUBoC	Clear	Target	3.219	0.188	1656	1074	2553
NI	Blurred	All	3.243	0.184	1750	1146	2673
NI	Blurred	Far	3.243	0.169	1750	1186	2582
NI	Blurred	Mid	3.236	0.190	1722	1112	2667
NI	Blurred	Near	3.227	0.184	1687	1104	2576
NI	Blurred	Target	3.260	0.170	1820	1230	2692
NI	Clear	All	3.248	0.186	1770	1153	2716
NI	Clear	Far	3.261	0.185	1824	1191	2793
NI	Clear	Mid	3.255	0.177	1799	1197	2704
NI	Clear	Near	3.256	0.173	1803	1211	2685
NI	Clear	Target	3.151	0.190	1416	914	2193
UB	Blurred	All	3.220	0.184	1660	1086	2535
UB	Blurred	Far	3.254	0.169	1795	1216	2649
UB	Blurred	Mid	3.295	0.180	1972	1303	2985
UB	Blurred	Near	3.236	0.180	1722	1138	2606
UB	Blurred	Target	3.027	0.152	1064	750	1510
UB	Clear	All	3.226	0.193	1683	1079	2624
UB	Clear	Far	3.245	0.176	1758	1172	2636
UB	Clear	Mid	3.242	0.167	1746	1189	2564
UB	Clear	Near	3.198	0.181	1578	1040	2393
UB	Clear	Target	3.162	0.197	1452	923	2286
UC	Blurred	All	3.204	0.181	1600	1054	2427
UC	Blurred	Far	3.214	0.190	1637	1057	2535
UC	Blurred	Mid	3.231	0.190	1702	1099	2636
UC	Blurred	Near	3.187	0.195	1538	982	2410
UC	Blurred	Target	3.238	0.166	1730	1180	2535
UC	Clear	All	3.213	0.191	1633	1052	2535

UC	Clear	Far	3.271	0.162	1866	1285	2710
UC	Clear	Mid	3.284	0.154	1923	1349	2742
UC	Clear	Near	3.260	0.156	1820	1271	2606
UC	Clear	Target	2.970	0.130	933	692	1259

Note. Task-Relevance Types: *Do Not Use Unique Blur or Clarity* = DNUUBoC. *No Instructions* = NI. *Use Blur* = UB. *Use Clarity* = UC. RT* = Untransformed Reaction Time. M = Marginal Means. GM = Geometric Mean. SD = Within-subject Standard Deviation. GSD = Geometric within-subject Standard Deviation. RT* has asymmetrical -1 and +1 GSDs because of the positive skew of the RT data when untransformed.

Table 18

Tukey HSD Comparisons: Task-Relevance x Resolution x Condition Interaction with Log_{10} (RT)

Task-Relevance	Resolution	Condition	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
UB	Blurred	Mid	ACD	3.294	0.017	3.260	3.327
UC	Clear	Mid	AB	3.285	0.017	3.252	3.319
UC	Clear	Far	ABC	3.274	0.019	3.236	3.312
DNUUBoC	Clear	Far	ABCDE	3.268	0.016	3.237	3.299
DNUUBoC	Blurred	Far	ABCDE	3.261	0.016	3.231	3.292
NI	Clear	Far	ABCDE	3.261	0.016	3.230	3.292
UC	Clear	Near	ABC	3.260	0.017	3.227	3.293
DNUUBoC	Clear	Mid	ABCDE	3.259	0.015	3.230	3.287
DNUUBoC	Blurred	Mid	ABCDE	3.257	0.015	3.229	3.286
NI	Clear	Near	ABCDE	3.256	0.015	3.227	3.285
DNUUBoC	Clear	All	ABCDE	3.255	0.015	3.226	3.284
NI	Clear	Mid	ABCDE	3.253	0.015	3.225	3.282
NI	Blurred	Target	ABCDE	3.252	0.016	3.221	3.283
UB	Blurred	Far	ABCDE	3.252	0.019	3.214	3.290
UB	Clear	Far	ABCDE	3.247	0.016	3.215	3.279
NI	Clear	All	ABCDEF	3.246	0.015	3.218	3.275
DNUUBoC	Clear	Near	ABCDEF	3.245	0.015	3.217	3.274
NI	Blurred	Far	ABCDEF	3.244	0.016	3.214	3.275
DNUUBoC	Blurred	All	ABCDEF	3.242	0.015	3.213	3.271
UB	Clear	Mid	ABCDE	3.241	0.015	3.211	3.271
NI	Blurred	All	ABCDEF	3.240	0.015	3.211	3.269
DNUUBoC	Blurred	Near	ABCDEF	3.238	0.015	3.210	3.267
UC	Blurred	Target	ABCDEFGH	3.238	0.016	3.206	3.270
UB	Blurred	Near	ABCDEG	3.236	0.017	3.203	3.269
DNUUBoC	Blurred	Target	ABCDEFGH	3.236	0.016	3.205	3.267
NI	Blurred	Mid	ABCDEF	3.235	0.015	3.207	3.264
UC	Blurred	Mid	CDEFGH	3.232	0.015	3.202	3.261

UB	Clear	All	BEG	3.226	0.015	3.196	3.256
NI	Blurred	Near	ABCDEF	3.224	0.015	3.196	3.253
UB	Blurred	All	BEG	3.221	0.015	3.191	3.251
DNUUBoC	Clear	Target	ABCDEFGH	3.220	0.016	3.189	3.250
UC	Blurred	Far	CDEFGH	3.214	0.016	3.182	3.246
UC	Clear	All	CDEFGH	3.212	0.015	3.183	3.242
UC	Blurred	All	DEFGH	3.205	0.015	3.175	3.235
UB	Clear	Near	BEFGH	3.198	0.015	3.168	3.228
UC	Blurred	Near	EFGH	3.187	0.015	3.157	3.217
UB	Clear	Target	FH	3.163	0.016	3.131	3.195
NI	Clear	Target	GH	3.153	0.016	3.122	3.184
UB	Blurred	Target	I	3.027	0.014	2.998	3.056
UC	Clear	Target	I	2.969	0.014	2.940	2.998

Note. Task-Relevance Types: *Do Not Use Unique Blur or Clarity* = DNUUBoC. *No Instructions* = NI. *Use Blur* = UB. *Use Clarity* = UC. Levels not connected by same letter are significantly different ($\alpha = 0.05$, Q = 3.92). Sq = Squares. Std Error = Standard Error.

As shown in Figure 18 and Table 18, across all *Task-Relevance Types*, the all-blur and all-clear conditions do not significantly differ. As in Exp. 1 and Peterson (2016) this once again suggests a lack of a legibility effect, this result is very important to show that attentional guidance does not occur when there is no resolution contrast, even when participants are instructed to use a specific resolution. Therefore, the all-blurred and all-clear conditions were used once again as baselines for the singleton conditions to see if there was an effect on selective attention, as in Exp. 1 and Peterson (2016).

Task-Relevance Type: No Instructions

When participants were not given instructions about resolution to help find the target, and resolution was non-predictive of the target location, then none of the blur conditions significantly differed. This is strong support for the *Blur is Ignored* hypothesis and replicates Exp. 1's findings for the set size of four and most of the findings for the set size of eight. However, the blurred near distractor condition was not responded to significantly faster than any other blurred conditions as it was in Exp. 1 for the set size of eight. Nevertheless, it was numerically the fastest blurred condition. The clear target singleton was responded to faster than all other conditions, and once again suggests that unique clarity captures attention, but the clear distractor singletons did not significantly differ from the all-clear condition. The eye movement analyses will further investigate the clear singleton conditions to see if they captured attention as was shown in Exp. 1. Together, these results are further strong support for the *Blur is Ignored* hypothesis that unique clarity captures attention and unique blur is ignored by selective attention. Thus, these findings should increase the confidence placed in the findings from Exp. 1 and Peterson (2016) by replicating the main findings.

Model comparisons for each quantitatively predicted hypothesis were performed to find which explained the Log_{10} (RT) data best. As in Exp. 1, the same fixed effect and random effects structures were used to make the models for each hypothesis. The BIC values for all three models, once again, strongly supported the *Blur is Ignored* model (BIC = -3024.8), which was 28.4 points lower than the *Blur Repels* (BIC = -2996.4), and 72.7 points lower than the *Blur Captures* (BIC = -2952.1) models. Table 19 shows the parameter estimates for the *Blur is Ignored* model. The likelihood ratio that the Log_{10} (RT) data was produced by the *Blur is Ignored* model is 1.5 x 10^6 and 6.1 x 10^{15} times more likely than the *Blur Repels* and *Blur Captures* models, respectively.

Table 19

Task-Relevance Type: No Instructions - Parameter Estimates Log_{10} (RT) - Blur is Ignored

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.153	0.016	4259	191.67	<.001
Hypothesis 3 - Blur is Ignored	0.034	0.003	7458	10.38	<.001
Log_{10} (Trial)	-0.019	0.005	7456	-3.50	<.001

Note. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Task-Relevance Type: Use Clarity

When participants were told to use unique clarity to find the target and unique clarity was present at the target 67% of the time, there was strong support for the *Blur is Ignored* hypothesis. As with the *No Instructions* task-relevance type, none of the blurred conditions significantly differed, indicating that unique blur was not guiding selective attention. The clear target condition was responded to faster than all other conditions. Interesting, the clear mid distractor condition was responded to significantly slower than the all-clear condition, possibly suggesting that the clear singleton was slowing down search by capturing attention away from the blurred target. Similarly, while the far and near clear distractor conditions did not significantly differ from the all-clear condition, they were the second and third slowest conditions. Therefore, the RT evidence is showing some support that unique clarity was selected for beyond just the clear target condition. Overall, these results support the *Blurred is Ignored* hypothesis that unique clarity captures attention and unique blur is ignored by attention.

As with the *No Instructions* task-relevance type, model comparisons for each quantitatively predicted hypothesis were performed to find which explained the Log_{10} (RT) data best. The same fixed effect and random effects structures were used to make the models for each hypothesis. The BIC values for all three models, once again, strongly supported the *Blur is Ignored* model (BIC = -3980.4), which was 28.4 points lower than the *Blur Repels* (BIC = -3422.0), and 72.7 points lower than the *Blur Captures* (BIC = -3176.3) models. Table 20 shows the parameter estimates for the *Blur is Ignored* model. The likelihood ratio that the Log_{10} (RT) data was produced by the *Blur is Ignored* model is 1.7×10^{121} and 4.1×10^{174} times more likely than the *Blur Repels* and *Blur Captures* models, respectively.

Table 20

Task-Relevance Type: Use Clarity - Parameter Estimates Log_{10} (RT) - Blur is Ignored

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	2.923	0.013	5588	230.76	<.001
Hypothesis 3 - Blur is Ignored	0.099	0.002	7082	52.07	<.001
Log_{10} (Trial)	-0.032	0.005	7082	-6.20	<.001

Note. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Task-Relevance Type: Use Blur

Of critical importance, when participants were instructed to use unique blur to find the target and unique blur was present at the target 67% of the time, there was strong support for the *Blur Captures* hypothesis. Most importantly, the blurred target condition was responded to faster than all other conditions. Interestingly, the mid blurred distractor condition was responded to significantly more slowly than the all-blurred condition, similarly to the *Use Clarity* result that the mid clear distractor condition was slower than the all-clear condition. None of the other blur conditions significantly differed. The clear target condition was responded to more quickly than all other clear conditions, except for the near clear distractor condition. This is an interesting finding, as it suggests that there may have been attentional capture to the near clear distractor followed by searching nearby blurred letters, which in this case had the target present adjacent to the clear distractor producing faster RTs.

Overall, the above result supported the *Blur Captures* hypothesis that unique clarity and unique blur capture attention. It also appears that unique blur was selected for to a greater degree than unique clarity when participants were using blur to find the target. This is very similar to the findings of Enns and MacDonald (2013, Exp. 4), who found that when blur was task-relevant, unique blur was detected faster than uniquely clear regions. Most importantly, this is strong evidence that resolution is not a search asymmetry, but instead that resolution's influence on attention is contingent upon its task-relevance. If resolution was a search asymmetry, then using unique blur should not have helped to find the target, and the blurred target singleton should have had a RT similar to the all-blur condition, as was found in the *No Instructions* task-relevance type, Exp. 1, and Peterson (2016). Instead, the results indicate that unique blur did guide attention because the blurred target condition was responded to faster than all other conditions. This suggests the existence of a reconfigurable resolution feature detector.

As with the *No Instructions* and *Use Clarity* task-relevance types, model comparisons for each quantitatively predicted hypothesis were performed to find which explained the Log_{10} (RT) data best. The same fixed effect and random effects structures were used to make the models for each hypothesis. For the first time, the BIC values compared across all three models strongly supported the *Blur Captures* model (BIC = -3322.6), which was 422.7 points lower than the *Blur Repels* (BIC = -2899.9), and 1203.4 points lower than the *Blur is Ignored* (BIC = -2119.2) models. Table 21 shows the parameter estimates for the *Blur Captures* model. The likelihood ratio that the Log_{10} (RT) data was produced by the *Blur Captures* model is 6.1×10^{91} and 2.1×10^{261} times more likely than the *Blur Repels* and *Blur is Ignored* models, respectively.

Table 21

Task-Relevance Type: Use Blur - Parameter Estimates Log_{10} (RT) - Blur Captures

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.102	0.013	7083	239.45	<.001
Hypothesis 1 - Blur Captures	0.062	0.002	7105	36.75	<.001
Log_{10} (Trial)	-0.034	0.005	7105	-6.31	<.001

Note. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Task-Relevance Type: Do Not Use Unique Blur or Clarity

When participants were instructed to not use unique blur or clarity to find the target and the resolution was non-predictive of the target location, none of the conditions significantly differed. The most impressive aspect of this finding is that only using instructions removed the attentional bias to unique clarity, which has been shown in Exp. 1, all three of the other task-relevance types (except the *Use Blur* condition), and Peterson (2016; Exp. 2). Importantly, the *No Instructions* task-relevance type had the same probability manipulation, such that resolution was non-predictive of the target location, as the *Do Not Use Unique Blur or Clarity* task-relevance type, yet with the change in instructions, none of the conditions differed from one another. Overall, these results support the *Blurred is Ignored* hypothesis because unique blur is not guiding attention, but unique clarity is also not guiding attention, therefore, this is not a great fit. However, it does suggest that the influence resolution has on guiding selective attention can be radically altered by the participants' goals only. This is because there was no probability manipulation difference between the *Do Not Use Unique Blur or Clarity* and *No Instructions* task-relevance types, yet the bias towards unique clarity was removed.

As with the previous three task-relevance types, model comparisons for each quantitatively predicted hypothesis was performed to find which explained the Log_{10} (RT) data best. An additional model called the *Unique Resolution is Ignored* hypothesis, which predicts that both unique blur and unique clarity are ignored. Therefore, search times are predicted to be the same whether all the items are blurred or presented clearly, or if a singleton in either resolution is present. This additional hypothesis was included for the model testing to see how it compares to the Blur is Ignored hypothesis. The same fixed effect and random effects structures were used to make the models for each hypothesis. The BIC values for all four models, strongly supported the *Unique Resolution is Ignored* model (BIC = -3983.4), which was 829.6 points lower than the *Blur is Ignored* model (BIC = -3153.8), and was 830.5 points lower than the *Blur Captures* (BIC = -3152.9) model, as well as 841.2 points lower than the Blur Repels (BIC = -3142.2) model. This is largely based on both the blurred and clear conditions not significantly differing from one another. Table 22 shows the parameter estimates for the *Unique Resolution is Ignored* model. The likelihood ratio that the Log_{10} (RT) data was produced by the *Unique Resolution is Ignored* model is 1.4×10^{180}, 2.2×10^{180}, and 4.6×10^{182} times more likely than the *Blur is Ignored*, *Blur Captures,* and *Blur Repels* models, respectively. Therefore, the quantitively predicted hypotheses show support for the *Blur is Ignored* and *Blur Captures* hypotheses, but not for the *Blur Repels* hypothesis.

Table 22

Task-Relevance Type: Do Not Use Unique Blur or Clarity - Parameter Estimates Log_{10} (RT) - Unique Resolution is Ignored

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.319	0.027	38.67	124.37	<.001
Hypothesis 4: Unique Resolution is Ignored	0	.	0	.	.
Log_{10} (Trial)	-0.034	0.011	23.59	-3.09	.005

Note. Parameter estimates for Hypothesis 4 – Unique Resolution is Ignored are zeroed because there is no variability in the predicts for each *Resolution x Condition*. Therefore, the intercept is the most important parameter estimate to predict each *Resolution x Condition* sets Log_{10} (RT). dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Eye Movement Analyses

As with Experiment 1, all the eye movement analyses were performed using trials that had correct responses and the presence of a resolution singleton. From these trials, the letter that was first fixated on each trial was identified. The proportion of first fixations to a singleton was created based on the letter that was first fixated on each trial either being the singleton or not. The analyses were conducted using R statistical software (version x64 3.3.1).

Whether resolution is a search asymmetry, and how resolution may guide selective attention were investigated using the proportion of first fixations to a singleton split by *Task-Relevance Type*. Figure 19 shows the proportion of first fixations to a singleton for *Task-Relevance Type x Resolution*, once again excluding the All condition, which does not have singletons. Eight multilevel logistic regressions were performed to separately analyze the proportion of first fixations to a singleton for each of the four levels of task-relevance type and two levels of resolution. All the fixed and random effects structures were the same as one another, where a constant was included as a fixed effect and varied across participants for the random effects structure. The proportion of first fixations to a singleton with 95% CIs was compared to chance (1/set size) to support or refute the alternative competing hypotheses.

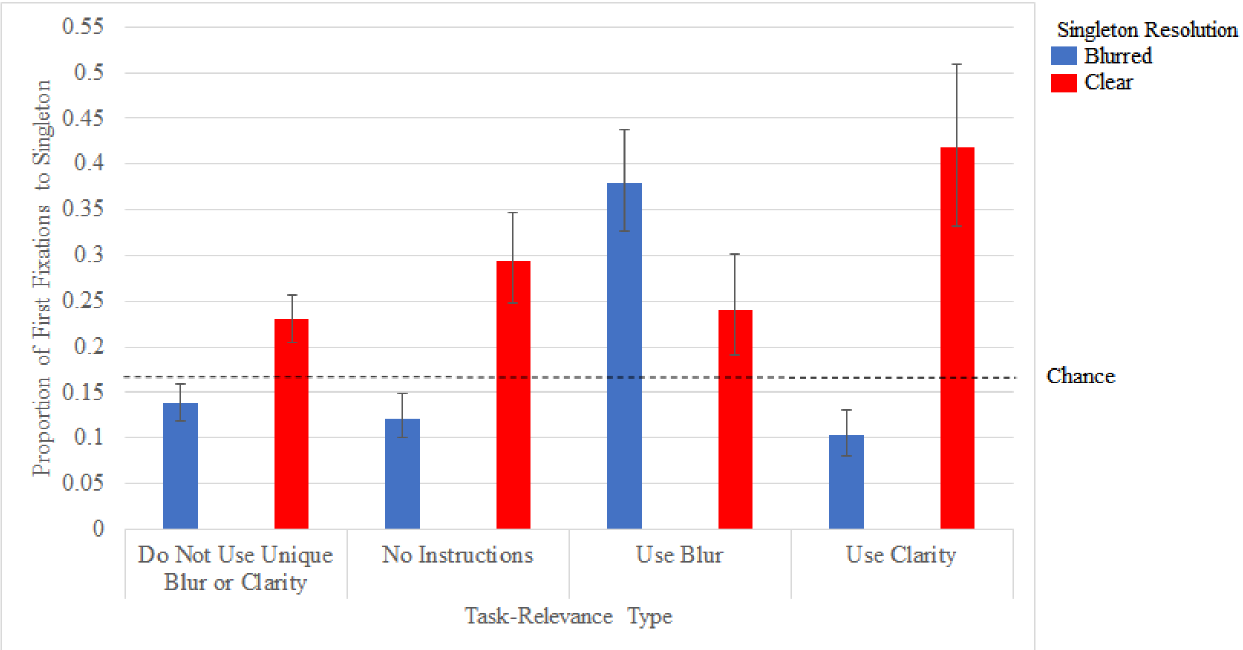

Figure 19. The mean proportion of first fixations to a singleton for *Task-Relevance Type x Resolution* with +/- 95% CI bars.

The *No Instructions* task-relevance type replicated the findings from Exp. 1. The proportion of first fixations to the clear singleton (*M* = 0.294, lower 95% CI = 0.247, higher 95% CI = 0.346) was significantly higher than chance (1/set size = 0.167). Likewise, as in Exp. 1, the blurred singleton (*M* = 0.122, lower 95% CI = 0.100, higher 95% CI = 0.149) was significantly less than chance. Thus, the first fixations to a singleton analysis for the *No Instructions* condition also replicated the results of Exp. 1. As in Exp. 1, this analysis shows strong support for the *Blur Repels* hypothesis that unique clarity captures attention and unique blur weakly repels attention.

The *Use Clarity* task-relevance type also supported the *Blur Repels* hypothesis with the proportion of first fixations to a singleton data. The proportion of first fixations to the clear singleton (*M* = 0.418, lower 95% CI = 0.332, higher 95% CI = 0.509) was significantly higher than chance. Similar to the *No Instructions* condition, the blurred singleton (*M* = 0.102, lower 95% CI = 0.080, higher 95% CI = 0.130) was significantly lower than chance. There was a much greater degree of selectivity for the clear singleton condition compared to the *No Instructions* task-relevance condition because the proportion of first fixations to a singleton increased by 0.124, suggesting that the manipulation to encourage using unique clarity facilitated the natural bias for unique clarity.

Most importantly, the *Use Blur* task-relevance type supported the *Blur Captures* hypothesis with the proportion of first fixations to a singleton data. Both the blurred singleton condition (*M* = 0.380, lower 95% CI = 0.326, higher 95% CI = 0.437) and the clear singleton condition (*M* = 0.241, lower 95% CI = 0.190, higher 95% CI = 0.301) were significantly higher than chance (chance proportion = 0.167). This strongly supports that resolution is not a search asymmetry, but instead resolution's influence on attention is contingent upon resolution's task-relevance. When unique blur is task-relevant, the RT and eye movement data suggests that it can be used to guide attention. This suggests the existence of a reconfigurable resolution feature detector.

The *Do Not Use Unique Blur or Clarity* task-relevance type supported the *Blur Repels* hypothesis. The proportion of first fixations to the clear singleton (*M* = 0.230, lower 95% CI = 0.205, higher 95% CI = 0.257) was significantly higher, and the blurred singleton (*M* = 0.138, lower 95% CI = 0.119, higher 95% CI = 0.159) was significantly less than chance (chance proportion = 0.167). This is an interesting finding, as it suggests that the measure of the proportion of first fixations to a singleton is more sensitive than the measure of RT. The RT results supported the *Blur is Ignored* hypothesis, but the eye movement data revealed that early on in the trial, blur guided attention by repelling it from its spatial location. This also suggests that only providing instructions is not enough to completely eliminate the attentional bias towards unique clarity and the weak repulsion of unique blur.

First Fixated Letter Location Relative to Blurred Singleton (No Instructions)

Four multilevel logistic regressions were performed to investigate if the first fixated letter's location relative to the blurred singleton data will replicate Exp. 1's findings using the *No Instructions* task-relevance type. Figure 20 shows the proportion of the first fixated letter's location relative to the blurred singleton for only the *No Instructions* task-relevance type. The four multilevel logistic regressions consisted of binomial data, which measured whether the first fixated letter was at the location of interest (1) or not (0). The locations of interest were: 1) blurred singleton or not, 2) letter near/adjacent to the blurred singleton or not, 3) letter mid distant from the blurred singleton or not, and 4) the letter farthest from the blurred singleton or not. The proportion of first fixation to each location and the 95% CIs (after being converted to proportions from logit space) were compared to chance. With a set size of six, the chance proportion of the first fixated letter to the blurred singleton or the farthest letter from the singleton is 0.167, because both have only one letter location. However, the chance proportion of first fixated letter to the near/adjacent and mid letters from the blurred singleton is 0.333, because there are two letters for each of these relative locations. The following analyses compare the actual data to the *Locally* versus *Equally Distributed* hypotheses.

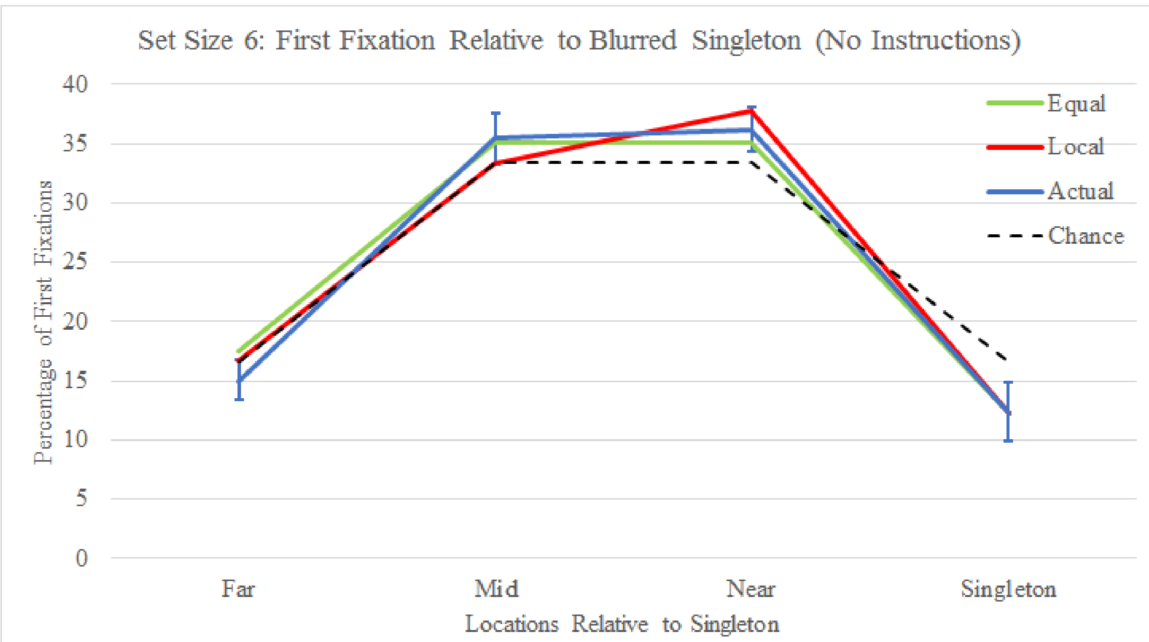

Figure 20. The mean percentage of first fixated letter's location relative to the blurred singleton for Location Relative to Singleton with 95% CI bars.

The set size of six first fixated letter's location relative to the blurred singleton replicated the findings from Exp. 1 supporting the *Locally Distributed* hypothesis. The proportion of first fixations to the blurred singleton (M = 0.122, lower 95% CI = 0.010, higher 95% CI = 0.149) was significantly lower than chance (chance proportion = 0.167), which was already known from the set size of six first fixation to a singleton analysis. The proportion of first fixations to a letter near/adjacent to the blurred singleton (M = 0.362, lower 95% CI = 0.343, higher 95% CI = 0.381) was significantly higher than chance (chance proportion = 0.333). Just as with the Exp. 1 results, this result alone is evidence supporting both the *Locally* and *Equally Distributed* hypotheses because both predict an increase in first fixation to the letters near/adjacent to the blurred singleton. However, the proportion of first fixations to the mid (*M* = 0.354, lower 95% CI = 0.333, higher 95% CI = 0.376), and far (*M* = 0.150, lower 95% CI = 0.134, higher 95% CI = 0.168), distant letters from the blurred singleton were not significantly different from chance (chance proportion = 0.250 Mid & = 0.125 Far). These results together support the *Locally Distributed* hypothesis because there was a spatial bias such that blur repelled attention towards nearby clarity. However, as discussed in Experiment 1, these results can also be interpreted as clarity, especially that close to blur, captured attention.

Learning to Use Blur

The reaction time and first fixation to a singleton results for the *Use Blur* task-relevance type supported that blur can be used to guide attention. However, when no instructions are provided, then blur weakly repels attention towards nearby clarity. This raises the question, is learning required to use blur when it is made task-relevant? To investigate this research question, an exploratory analysis was performed. A logistic regression was performed measuring Proportion First Fixated Singleton (Fixated Singleton = +1, Fixated Nonsingleton = 0) by each *Task-Relevance Type*, the *Singleton Resolution*, and *Trial (number)*. The independent variables were effect coded: *Task-Relevance Type* (*Do Not Use Unique Blur or Clarity* = '+1, 0, 0', *No Instructions* = '0,+1,0', *Use Blur* = '0,0,+1', & *Use Clarity* = '-1,-1,-1'), *Singleton Resolution* (Blurred = +1, Clear = -1), and *Trial* was mean-centered. How often the singleton was fixated first for each trial was measured for blurred versus clear singletons across each task-relevance type. Practice and experimental trials were merged together to measure learning throughout the entire experimental session. The practice trials represent the first 80 trials, while the remaining 320 trials all came from the experimental trials, for a total of 400 trials. Figure 21 presents the Proportion First Fixated Singleton by each *Task-Relevance Type* and the *Singleton Resolution* across *Trials*.

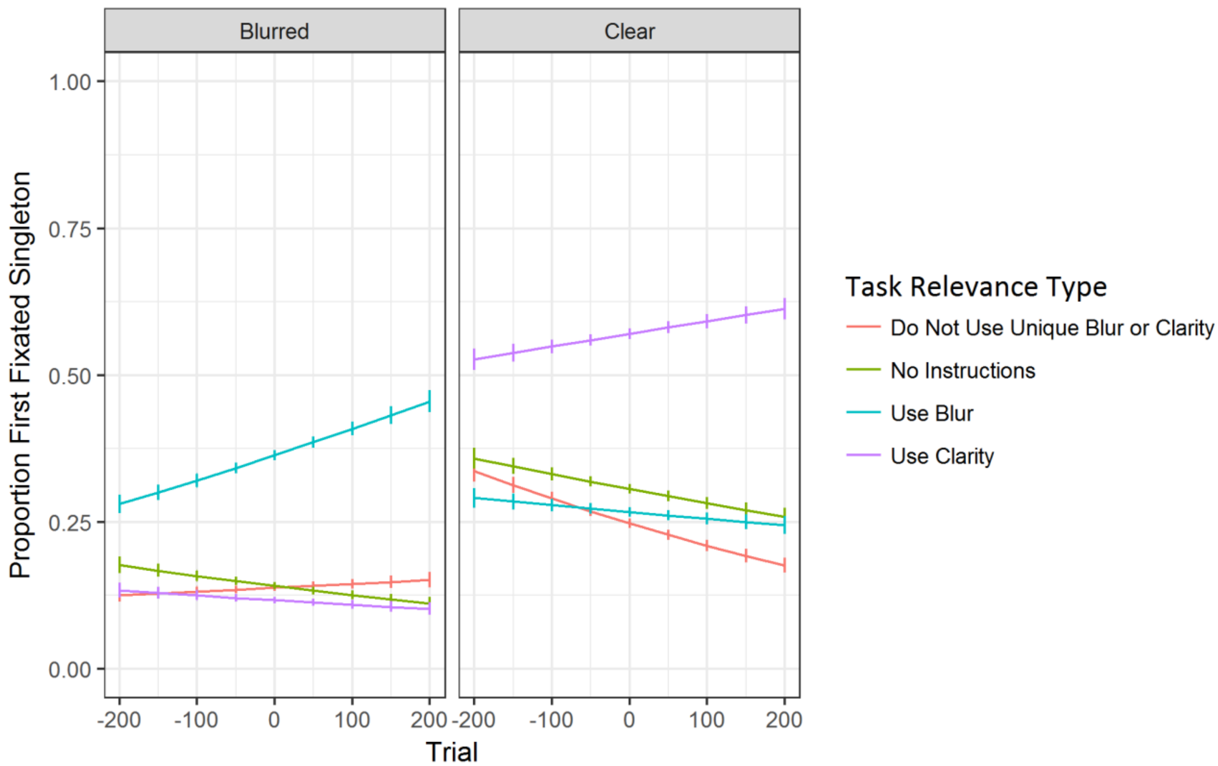

Figure 21. Predicted proportion First Fixated Singleton by each *Task Relevance Type* and the *Singleton Resolution* across *Trials*. *Trial* was centered, (*Trial* – 202.348) = *Trial*.

Table 23 shows that all of the main effects, two-way, and three-way interactions were significant. The main finding is that there was a significant three-way interaction for *Task-Relevance Type x Singleton Resolution x Trial*, $\chi 2(3) = 42.32$, $p < .001$. The parameter estimates are presented in Table 24 for comparison between the conditions.

Table 23

Effect Tests from the First Fixated Singleton Logistic Regression

Source	DF	L-R ChiSquare	Prob>ChiSquare
Trial	1	5.86	0.016
TRT	3	348.30	<.001
Trial*TRT	3	32.16	<.001
SR	1	831.49	<.001
Trial*SR	1	9.40	0.002
TRT*SR	3	1100.32	<.001
Trial*TRT*SR	3	42.32	<.001

Note. Task-Relevance Type (TRT). Singleton Resolution (SR).

Table 24

Parameter Estimates from the First Fixated Singleton Logistic Regression

Fixed Effects	Estimates	Std Error	L-R ChiSquare	Prob>ChiSquare
Intercept	-1.042	0.032	1207.60	<.001
Trial	-3.4E-04	1.4E-04	5.86	0.016
TRT(DNUUBoC)	-0.362	0.028	171.58	<.001
TRT(NI)	-0.202	0.027	56.50	<.001
TRT(UB)	0.325	0.025	161.94	<.001
Trial*TRT(DNUUBoC)	-4.7E-04	2.5E-04	3.59	0.058
Trial*TRT(NI)	-0.001	2.4E-04	14.84	<.001
Trial*TRT(UB)	0.001	2.2E-04	20.36	<.001
SR(B)	-0.446	0.016	831.49	<.001
Trial*SR(B)	4.3E-04	1.4E-04	9.40	0.002
TRT(DNUUBoC)*SR(B)	0.085	0.028	8.96	0.003
TRT(NI)*SR(B)	-0.049	0.027	3.23	0.073
TRT(UB)*SR(B)	0.671	0.025	720.08	<.001
Trial*TRT(DNUUBoC)*SR(B)	0.001	2.5E-04	14.03	<.001
Trial*TRT(NI)*SR(B)	-0.001	2.4E-04	4.52	0.034
Trial*TRT(UB)*SR(B)	0.001	2.2E-04	13.99	<.001

Note. Task-Relevance Type (TRT): *Do Not Use Unique Blur or Clarity* = DNUUBoC, *No Instructions* = NI, *Use Blur* = UB, *Use Clarity* = UC . Singleton Resolution (SR): Blurred = B, Clear = C. Model was performed using effect coding Task-Relevance Type [(*Do Not Use Unique Blur or Clarity* = '+1, 0, 0', *No Instructions* = '0,+1,0', *Use Blur* = '0,0,+1', & *Use Clarity* = '-1,-1,-1') (Singleton Resolution (Blurred = +1, Clear = -1)]. Trial was centered, (Trial – 202.348) = Trial. Std Error = Standard Error.

As noted above for Figure 21, when participants were instructed to use blur they started above chance (1/set size = 0.167). Furthermore, as the experiment progressed, they showed significant improvement in their ability to use blur during search, indicated by the increase in blur singletons being fixated first by the end of the experimental session. These results supported that learning to use blur did occur. The results suggested that blur can be used very early on to guide search based on instructions accompanied with a valid probability manipulation. This was shown by the blur singletons being fixated first above chance from the beginning of the practice trials, but also that there was room for improvement.

Interestingly, when participants were instructed to use unique clarity, they started fixating the clear singletons first at a higher level (0.53) than the proportion of blurred singletons fixated first by the end of the experiment (0.45). There was not as significant of improvement in learning to use clarity though there was a trend to improve some. It seems that this is a case where unique blur started closer to the floor with more room to improve and unique clarity started closer to the ceiling where there was less room for improvement and thus learning was seen to a lesser degree.

The other three task-relevance types had very little change to fixating a blurred singleton across the experimental session and hovered around chance (0.167). The *Do Not Use Unique Blur or Clarity* and *No Instructions* task-relevance types showed a trend to decrease the capture to clear singletons across the experimental session. Surprisingly, this trend was found to a much lesser degree with the *Use Blur* condition, which may be because the *Use Blur* condition started at the lowest proportion of capture to clear singletons compared to the other three Task-relevance types. This analysis shows that while the task-relevance manipulation (i.e., instructions + probability manipulation) had strong effects on attention, it did require some learning for the *Use Blur* condition, though the instructions had an immediate effect from the very beginning of practice.

Conditionalizing Time to Fixate a Singleton Target based on First Fixated Letter's Resolution and Task-Relevance

How long did it take to fixate a blurred target singleton when using blur to guide search compared to fixating a clear target singleton when using clarity to guide search, specifically when the target singleton was the first letter fixated? To investigate this research question, the time from the onset of the letters to when the first fixated letter was a blurred target singleton in the *Use Blur* Task-Relevance Type or a clear target singleton in the *Use Clarity* Task-Relevance Type occurred. Only the target singleton conditions were included because fixating the target was needed to correctly complete the task, whereas distractor conditions did not require fixating a singleton to complete the task. Additional data cleaning was required to remove first fixations that started less than 550 msec into the trial. Therefore, a total of 143 (3.5%) trials were removed from 4053 trials, which left a total of 3,910 trials for the analysis. The cutoff of 550 msec was selected because fixations that started during the gray screen could occur ~500 msec before the letters were presented and an additional 50 msec was included for time it would take for a saccade to move to the letter. This is a very conservative cutoff which only removed fixation start times that were made to letters that did not exist or when there was inadequate time to process the letter before making a saccade towards it.

A linear multilevel model with effect coding was performed in JMP Pro 12. The model included the Time to Fixate a Singleton Target as the dependent measure, which was the time it took to fixate a singleton target, when it was the first letter searched, from the time when all the letters were displayed. Figure 22 shows the mean Time to Fixate a Singleton Target in msec and ± 95% CI for both *Task-Relevance Types* (*Use Blur* vs. *Use Clarity*). The independent variables were *Task-Relevance Type* (*Use Blur* = +1, *Use Clarity* -1), as well as *Log₁₀ (Trial)*, which were included as main effects. The random effects structure included the main effects for *Task-Relevance Type* and *Log₁₀ (Trial)* across participants with adjusted R^2 = .32, RMSE = 118. Table 25 provides the model's parameter estimates.

Figure 22. The mean time to fixate a singleton target from the onset of the letters. The time it took tot fixated the blurred target singleton in the *Use Blur* Task-Relevance Type or the clear target singleton in the *Use Clarity* Task-Relevance Type as the first item with +/- 95% CI bars.

Table 25

Parameter Estimates for Time to Fixate Target Linear Multilevel Model

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	412.285	30.231	50.70	13.64	<.001
TRT(UB)	-2.744	10.812	32.01	-0.25	0.800
Log_{10} (Trial)	-13.431	13.318	39.32	-1.01	0.319

Note. Task-Relevance Type = TRT. *Use Blur* = UB. Model was created using effect coding (Task-Relevance Type: *Use Blur* = +1, *Use Clarity* = -1). dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

As presented in Table 25, there was no main effect for *Log_{10} (Trial)*, $F(1, 39.32) = 1.02$, $p = 0.319$, indicating the time to fixate a singleton target did not significantly change across the *Use Blur* and *Use Clarity* conditions. As shown in Figure 22 and Table 25, there was no main effect for *Task-Relevance Type*, $F(1, 32.0) = 0.06$, $p = 0.801$, which suggests that using blur to fixate a blurred target singleton first was not significantly different than using clarity to fixate a clear target singleton first. Therefore, the time to fixate a singleton target results supported that resolution is not a search asymmetry. This is based on the fact that, when resolution was made task-relevant, the blurred and clear target singletons did not significantly differ in their times when first fixated during search. This suggests the existence of a reconfigurable resolution feature detector.

Conditionalizing Log_{10} (RT) based on the First Fixated Letter's Resolution

An exploratory multilevel linear model was performed to investigate if using blur or clarity to guide search produced more efficient search when the first letter fixated was the same resolution as the target singleton condition. Also, what happens to RT when the opposite resolution of the target singleton condition is first fixated. To investigate these research questions, Log_{10} (RT) was the dependent measure compared between the *Use Blur* and *Use Clarity* Task-Relevance Types, specifically with the target singleton conditions. Only the target singleton conditions were included because fixating the target is needed to correctly complete the task, whereas distractor conditions did not require fixating a singleton to complete the task. The data set was cleaned with the same technique as the Conditionalizing Time to Fixate a Target Singleton data set.

A linear multilevel model with effect coding was performed in JMP Pro 12. The model included Log_{10} (RT) as the dependent measure. Figure 23 shows the mean Log_{10} (RT) and ± 95% CI for *Task-Relevance Type x Target Resolution x Resolution First Fixated*. The independent variables: *Task-Relevance Type* (*Use Blur* = +1, *Use Clarity* -1), *Target Resolution* (Blur = +1, Clarity -1), and *Resolution First Fixated* (Blur = +1, Clarity = -1), which were included as three main effects, three two-way interactions, and one three-way interaction. Additionally, *Log_{10} (Trial)* was included as a main effect. The random effects structure included the main effects and interaction for *Task-Relevance Type x Target Resolution x Resolution First Fixated* across participants with adjusted R^2 = .49, RMSE = 0.14. *Log_{10} (Trial)* was not included in the random effects structure due to a lack of degrees of freedom, but it was included in the fixed effect structure. Table 26 provides the model's parameter estimates.

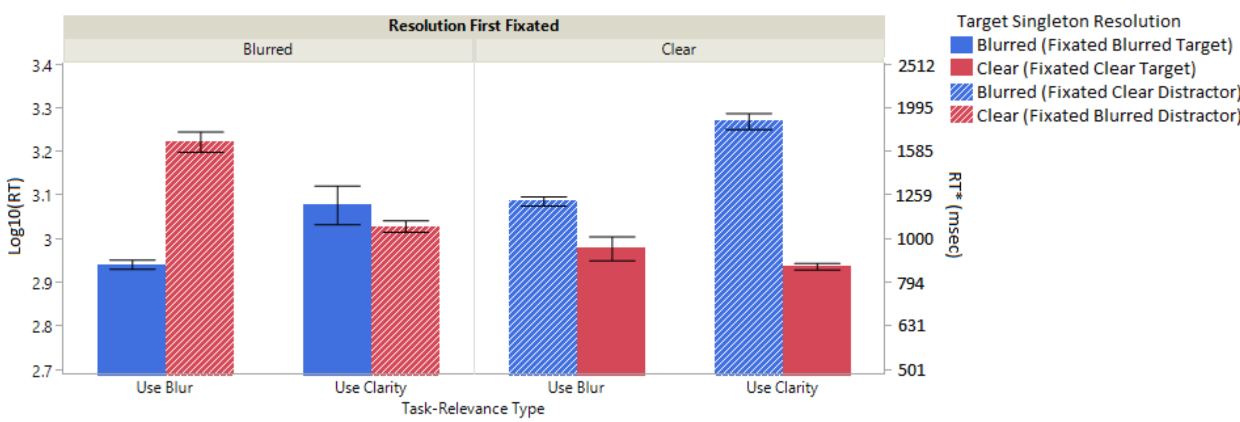

Figure 23. The mean Log_{10} (RT) for *Task-Relevance Type x Target Resolution x Resolution First Fixated* with +/- 95% CI bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale. Blurred Target Singleton condition has blue bars (Solid Blue Bars = Blurred Target Singleton was fixated first; Striped Blue Bars = Clear Distractor Nonsingleton letter was fixated first). Clear Target Singleton condition has red bars (Solid Red Bars = Clear Target Singleton was fixated first; Striped Clear Bars = Blurred Distractor Nonsingleton letter was fixated first).

Table 26

Parameter Estimates for Log_{10} (RT) Task-Relevance Type x Target Resolution x Resolution First Fixated Linear Multilevel Model

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	3.172	0.015	257.50	215.50	<.001
TRT(UB)	-0.011	0.010	48.02	-1.11	0.273
TR(B)	0.025	0.005	52.85	4.56	<.001
TRT(UB)*TR(B)	-0.069	0.005	52.68	-12.60	<.001
RFF(B)	0.003	0.004	61.36	0.72	0.475
TRT(UB)*RFF(B)	0.022	0.004	69.72	5.61	<.001
TR(B)*RFF(B)	-0.083	0.005	72.01	-18.29	<.001
TRT(UB)*TR(B)*RFF(B)	-0.008	0.005	71.39	-1.84	0.070
Log_{10} (Trial)	-0.049	0.005	3792.00	-9.08	<.001

Note. Task-Relevance Type = TRT. *Use Blur* = UB. Target Resolution = TR. Blurred = B. Resolution First Fixated = RFF. Model was performed using effect coding [(Task-Relevance Type: *Use Blur* = +1, *Use Clarity* = -1); (Target Resolution: Blurred = +1, Clear = -1); (Resolution First Fixated: Blurred = +1, Clear = -1)]. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Log_{10} (RT) significantly decreased across the experimental trials, *Log_{10} (Trial)*, $F(1, 3792) = -9.08$, $p < .001$, indicating that the participants made faster responses as the experiment progressed. There was no main effect for *Task-Relevance Type*, $F(1, 48.0) = 1.23$, $p = 0.273$, or *Resolution First Fixated*, $F(1, 61.4) = 0.52$, $p = 0.475$, which suggests that fixating the blurred and clear target singletons' was not significantly influenced based solely on the *Task-Relevance Type* and the *Resolution First Fixated*. However, there was a significant main effect for *Target Resolution*, $F(1, 52.9) = 20.80$, $p < .001$, as well as all of the two-way interactions: *Task-Relevance Type x Target Resolution*, $F(1, 52.7) = 158.89$, $p < .001$, *Task-Relevance Type x Resolution First Fixated*, $F(1, 69.7) = 31.53$, $p < .001$, and *Target Resolution x Resolution First Fixated*, $F(1, 72.0) = 334.69$, $p < .001$. All of the two-way interactions were further analyzed with Tukey HSD tests (see Table 27, 28, & 29, respectively). The three-way interaction, *Task-Relevance Type x Target Resolution x Resolution First Fixated*, $F(1, 71.4) = 3.39$, $p = .070$, was not significant.

Table 27

Tukey HSD Comparisons of Log$_{10}$ (RT) as a function of Task-Relevance Type x Target Resolution

TRT	TR	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Use Clarity	Blurred	A	3.176	0.017	3.14	3.21
Use Blur	Clear	B	3.104	0.016	3.07	3.14
Use Blur	Blurred	C	3.016	0.014	2.99	3.05
Use Clarity	Clear	C	2.987	0.015	2.96	3.02

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, Q = 2.653). Task-Relevance Type = TRT. Target Resolution = TR. Sq = Squares. Std Error = Standard Error.

Table 28

Tukey HSD Comparisons of Log$_{10}$ (RT) as a function of Task-Relevance Type x Resolution First Fixated

TRT	RFF	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Use Clarity	Clear	A	3.101	0.014	3.07	3.13
Use Blur	Blurred	AB	3.085	0.014	3.06	3.11
Use Clarity	Blurred	BC	3.062	0.016	3.03	3.09
Use Blur	Clear	C	3.035	0.015	3.01	3.07

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, Q = 2.632). Task-Relevance Type = TRT. Resolution First Fixated = RFF. Sq = Squares. Std Error = Standard Error.

Table 29

Tukey HSD Comparisons of Log$_{10}$ (RT) as a function of Target Resolution x Resolution First Fixated

TR	RFF	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Blurred	Clear	A	3.176	0.0114	3.1533	3.1987
Clear	Blurred	B	3.13158	0.0116	3.1085	3.1546
Blurred	Blurred	C	3.01562	0.01411	2.9878	3.0434
Clear	Clear	D	2.96011	0.01293	2.9345	2.9857

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, Q = 2.637). Target Resolution = TR. Resolution First Fixated = RFF. Sq = Squares. Std Error = Standard Error.

As shown in Table 27 and Figure 23, the *Task-Relevance Type x Target Resolution* (which collapses across levels of *Resolution First Fixated* factor), reaction times were not significantly different between searching for a blurred target singleton when using blur to guide search than searching for a clear target singleton when using clarity to guide search. This is strong evidence that resolution is not a search asymmetry, but contingent upon resolution's task-relevance. However, interestingly, reaction times were longer when using clarity to guide attention when the target was a blurred singleton compared to using blur to guide attention when the target was a clear singleton. This suggests that both blur and clarity can be used to guide search, but using clarity may be a more sustainable as a search strategy based on it taking longer to find a blurred target singleton. This may indicate that it is easier to avoid searching for a blurred letter than a clear letter when using blur to guide search.

As shown in Table 28 and Figure 23, the *Task-Relevance Type x Resolution First Fixated* interaction (which collapses across levels of the *Target Singleton Resolution* factor) is mostly driven by very slow reaction times in two types of trials. The two types of trials are the *Use Blur* Task-Relevance Type when a blurred letter is fixated first, but the target is a clear target singleton, and the complementary case of the *Use Clarity* Task-Relevance Type when a clear letter is fixated first, but the target is a blurred target singleton. It is not surprising that these two types of trials produced the two slowest reaction times because if using blur to guide search, then when there is a clear target singleton, the participant should ideally fixate it last, and vice versa when using clarity during a blurred target singleton trial. In the *Task-Relevance Type x Resolution First Fixated* interaction, the slowest reaction time trials were merged with the two types of trials that had the fastest reaction times. The two types of trials that had the fastest reaction times were when participants used blur and fixated a blurred target singleton or used clarity and fixated a clear target singleton first. Both the slowest and the fastest reaction times were merged together in the *Task-Relevance Type x Resolution First Fixated* interaction, which resulted in the *Use Clarity – Resolution First Fixated* = Clear and *Use Blur – Resolution First Fixated* = Blur being the slowest reaction times. Conversely, using blur to guide attention and fixating a clear letter first produced the fastest reaction time, though not significantly faster than using clarity to guide attention and fixating a blurred letter first. As shown in Table 28, using blur to guide attention and fixating a clear letter first may produce the fastest reaction time because 1) fixating a clear letter first in a clear target singleton trial means the target is fixated, which should result in a very fast reaction time, and 2) fixating a clear letter first in a blurred target singleton trial may result in fixating a blurred letter as the second letter fixated, which would be the target, if the search strategy to use blur is regained. This would result in the target being fixated as the second letter in the search, which should produce a fast reaction time. This would also predict that there should be an increase in blurred target singletons as the second letter fixated during search. Based on earlier evidence from the First Fixation to a Singleton results, it seems likely that the first clear letter that is fixated is a clear letter adjacent to the blurred target singleton. This is because failing to use blur to guide attention at the start of the trial suggests that search may have occurred in a similar fashion to when no instructions were given related to resolution. The First Fixation to a Singleton results have shown that when no instructions are provided, the adjacent clear letters to a blurred singleton are fixated most often.

As shown in Table 29 and Figure 23, the *Target Resolution x Resolution First Fixated* interaction (which collapses across levels of *Task-Relevance Type*) mean reaction times were all significantly different. Not surprisingly, when a letter of the opposite resolution to the target was fixated first, it produced the longest reaction times. The clear target singleton condition where a blurred letter was fixated first was significantly faster than the blurred target singleton condition where a clear letter was fixated first. However, both were significantly longer than the blurred letter (target) being fixated in the blurred target singleton and clear letter (target) being fixated in the clear target singleton trials. The most interesting finding is that when a clear target singleton was present, and a clear letter (i.e., the target) was fixated first, it was responded to faster than when a blurred target singleton was present, and a blurred letter (i.e., the target) was fixated first. This result is interesting because of the previous Time to Fixate a Singleton Target results, which indicated that there was not a difference in the time to start fixating the clear or blurred target singletons when task-relevant.

One possible explanation that the mean Log_{10} (RT) for a clear target singleton that was fixated first was responded to faster than when a blurred target singleton was fixated first, is that there is a difference in attentional deployment. It may take more time to deploy attention to the blurred singleton when participants are using clarity than to the clear singleton when participants are using blur to guide attention, or vice versa. The Time to Fixate a Singleton Target results did indicate that there was not a significant difference in the time to start fixating the clear or blurred target singletons when task-relevant. However, what happens to the time to start fixating the clear or blurred target singleton when the target is the opposite resolution than what is task-relevant (e.g., fixated the blurred target singleton, when participants were supposed to use clarity to guide search). This possible explanation for the data was investigate, but there was not a significant difference for the Time to Fixate a Singleton Target when the clear target singleton was fixated first, when participants were supposed to be using blur to guide search compared to the blurred target singleton being fixated first, when participants were supposed to be using clarity to guide search (see Appendix 2 for full details). Therefore, the difference in Log_{10} (RT) does not appear to be due to a delay in attentional deployment.

What was driving the difference between the reaction times? It appears that when a participant was supposed to use clarity to guide search, but instead fixated a blurred letter first during a blurred target singleton trial, it produced a longer reaction time than when the same error was made in the opposite resolution (*Use Blur – Resolution First Fixated* = Clear – Clear Target Singleton). This difference is not explained be a longer attentional deployment of attention to the blurred target singleton, when participants are using clarity to guide attention. Another possibility is that after fixating the blurred target singleton the search continued more often than when a clear target singleton was fixated first when the participant was supposed to be use blur to guide search. Figure 24 shows evidence from a Poisson regression, which measured the Total Number of Items Search, with independent variables *Task-Relevance Type* (*Use Blur* & *Use Clarity*), *Target Resolution* (Blur & Clear), and *Resolution First Fixated* (Blur or Clear).

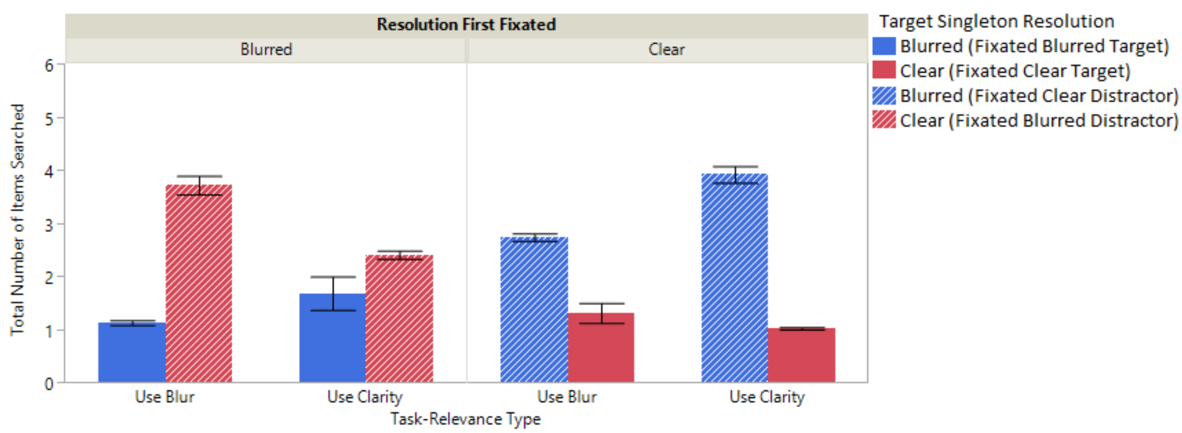

Figure 24. Average total number of items searched to find target for *Task-Relevance Type x Resolution x Resolution First Fixated* with 95% CI bars. Blurred Target Singleton condition has blue bars (Solid Blue Bars = Blurred Target Singleton was fixated first; Striped Blue Bars = Clear Distractor Nonsingleton letter was fixated first). Clear Target Singleton condition has red bars (Solid Red Bars = Clear Target Singleton was fixated first; Striped Clear Bars = Blurred Distractor Nonsingleton letter was fixated first).

A contrast between the *Use Clarity – Resolution First Fixated* = Blur – Blurred Target Singleton condition had a nearly significantly greater mean number of items searched than the *Use Blur – Resolution First Fixated* = Clear – Clear Target Singleton condition, $t(1) = 3.82$, $p = 0.051$. This trend is a possible explanation for the increased Log_{10} (RT) for a blurred target singleton trial when a blurred letter was first fixated compared to a clear target singleton trial when a clear letter was first fixated.

Average Number of Items Searched to Fixate the Target for the All and Target Conditions as a Function of Task-Relevance Types

This analysis compared the average number of items fixated to find the target in the All Blur, All Clear, Blurred Target Singleton, and Clear Target Singleton conditions for each Task-Relevance Type. The average number of items fixated to find the target for the All conditions in each Task-Relevance Type was used as a baseline to compare to the target singleton with the same resolution. If participants in the Target Singleton condition searched less items than the All condition to find the target, then that would be evidence for *Capture* in either the clear or blurred target singleton conditions. If there were more items searched for in the Target Singleton condition compared to the All condition, then that would be evidence for *Repelling* in either the clear or blurred target singleton conditions. If the Target Singleton and All conditions' number of items searched to find the target does not significantly differ, then that would be evidence in support of *Ignored* in either the clear or blurred target singleton conditions.

A Poisson regression with effect coding was performed in JMP Pro 12. The model included the number of items fixated, which came from trials with correct responses. Figure 25 shows the mean number of items fixated and ± 95% CI for *Task-Relevance Type x Resolution x Condition*. The independent variables were effect coded: *Task-Relevance Type* (*Do Not Use Unique Blur or Clarity* = '+1,0,0', *No Instructions* = '0,+1,0', *Use Blur* = '0,0,+1', *Use Clarity* = '-1,-1,-1'), *Resolution* (Blur = +1, Clarity -1), and *Condition* (All = +1, Target = -1), which were included as three main effects, three two-way interactions, and one three-way interaction. Table 30 provides the model's parameter estimates.

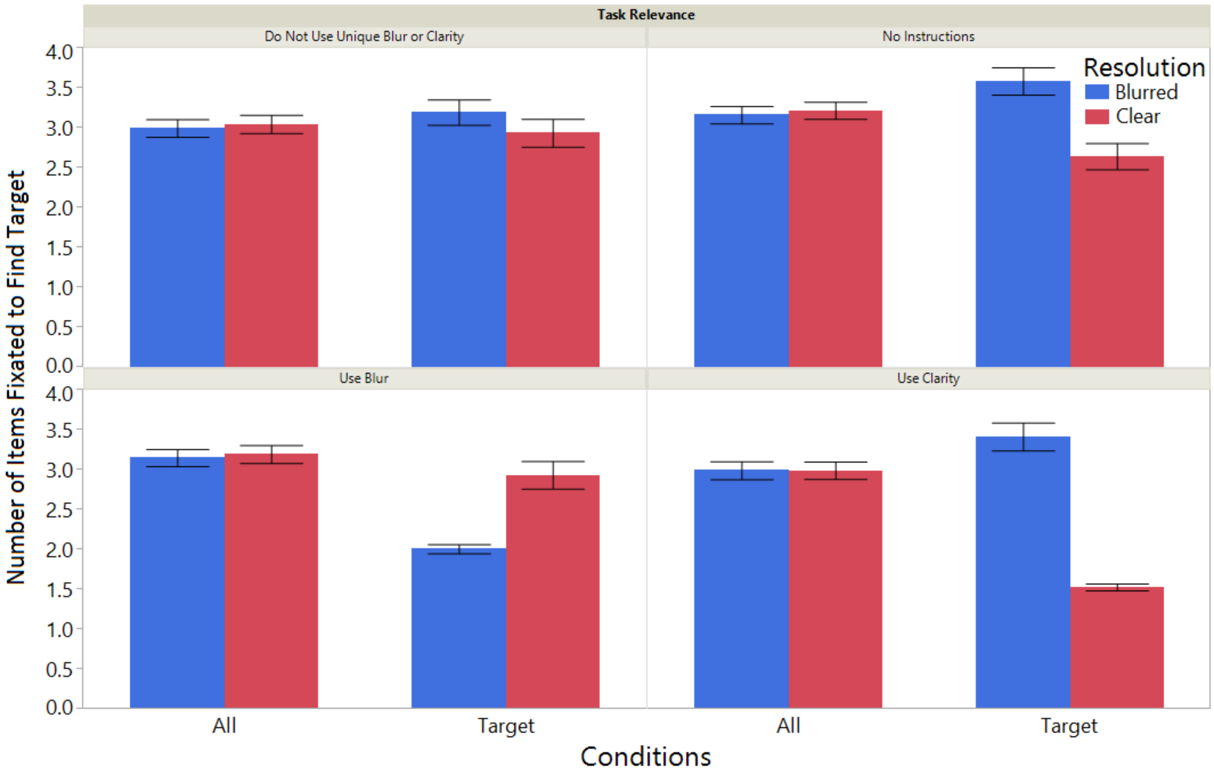

Figure 25. Average number of items fixated to find the target for *Task-Relevance Type x Resolution x Condition* with 95% CI bars.

Table 30

Parameter Estimates for Average Number of Items Fixated to Find the Target Linear Multilevel Model

Fixed Effects	Estimates	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	1.060	0.006	22043.1	<.001
TRT(DNUUBoC)	0.053	0.011	24.56	<.001
TRT(NI)	0.083	0.010	64.82	<.001
TRT(UB)	-0.039	0.010	16.23	<.001
Res(B)	0.048	0.006	67.31	<.001
TRT(DNUUBoC)*Res(B)	-0.031	0.011	8.28	0.004
TRT(NI)*Res(B)	0.024	0.010	5.57	0.018
TRT(UB)*Res(B)	-0.146	0.010	224.43	<.001
Cond(A)	0.070	0.006	145.85	<.001
TRT(DNUUBoC)*Cond(A)	-0.077	0.011	50.38	<.001
TRT(NI)*Cond(A)	-0.052	0.010	25.75	<.001
TRT(UB)*Cond(A)	0.064	0.010	44.36	<.001
Res(B)*Cond(A)	-0.054	0.006	85.45	<.001
TRT(DNUUBoC)*Res(B)*Cond(A)	0.028	0.011	7.05	0.008
TRT(NI)*Res(B)*Cond(A)	-0.027	0.010	6.84	0.009
TRT(UB)*Res(B)*Cond(A)	0.145	0.010	220.62	<.001

Note. Task-Relevance Type = TRT. *Do Not Use Unique Blur or Clarity* = DNUUBoC. *No Instructions* = NI. *Use Blur* = UB. *Use Clarity* = UC. Resolution = Res. Blurred = B. Clear = C. Condition = Cond. All = A. Model was performed using effect coding [(Task-Relevance Type: DNUUBoC = '+1,0,0', NI = '0,+1,0', UB = '0,0,+1', UC = '-1,-1,-1'); (Resolution: Blurred = +1, Clear = -1); (Condition: All = +1, Target = -1). Std Error = Standard Error.

All of the main effects, two-way interactions, and the three-way interaction were highly significant (all p-values < .001). Therefore, contrasts were performed to compare significant differences between specific pairings of the average number of items fixated during search. The Blurred Target condition had significantly more items fixated to find the target than the All Blurred condition in the Task-Relevance Types of *Do Not Use Unique Blur or Clarity*, $t(4) = 3.28$, $p = 0.070$, *No Instructions*, $t(4) = 15.12$, $p < .001$, and *Use Clarity*, $t(4) = 14.60$, $p < .001$. However, the Blurred Target condition had significantly less items fixated to find the target than the All Blurred condition in the Task-Relevance Type of *Use Blur*, $t(4) = 290.02$, $p < .001$. Together these results suggested that blur repels attention, unless it is task-relevant, in which case it can be selected for and used to guide search.

The Clear Target condition required significantly less items fixated to find the target than the All Clear condition in the Task-Relevance Types of *No Instructions*, $t(4) = 32.42$, $p < .001$, *Use Blur*, $t(4) = 6.16$, $p = 0.013$, and *Use Clarity*, $t(4) = 539.83$, $p < .001$. However, the Clear Target condition average number of items fixated to find the target did not significantly differ from the All Clear condition in the Task-Relevant Type of *Do Not Use Unique Blur or Clarity*, $t(4) = 1.06$, $p = 0.303$. These results suggest that clarity will capture attention and guide search, unless specifically instructed to not use clarity to perform the search. Unique clarity's capture was also greatly diminished when participants were instructed to use blur. This is evidence that prioritizing blur has a negative impact on clarity's natural bias to be used during search. The results suggested that search for a blurred or clear singleton simultaneously may be a very difficult task and possible only one resolution singleton can be search for at any given moment.

Across all the Task-Relevance types, the All Blurred and All Clear conditions were not significantly different, which is strong evidence that in order for resolution to guide attention there needs to be resolution contrast. In other words, if resolution is going to guide attention, then both blur and clarity must be present.

The Blurred Target condition required significantly more items to be fixated to find the target than the Clear Target condition in the Task-Relevance Types of *Do Not Use Unique Blur or Clarity*, $t(4) = 4.13$, $p = 0.042$, *No Instructions*, $t(4) = 61.27$, $p < .001$, and *Use Clarity*, $t(4) = 506.17$, $p < .001$. However, the Blurred Target condition required significantly fewer items fixated to find the target than the Clear Target condition in the Task-Relevance Type of *Use Blur*, $t(4) = 120.82$, $p < .001$. The main finding from this set of results is that when unique blur is specifically task-relevant, it can be used to guide attention during search, and it guides attention more than unique clarity under such circumstances.

The final comparison of the items fixated to find the target was between the *Use Blur – Blurred Target* compared to the *Use Clarity – Clear Target* condition. The *Use Blur – Blurred Target* condition required significantly more items fixated to find the target then the *Use Clarity – Clear Target* condition, $t(1) = 108.30$, $p < .001$. This result suggested that unique clarity is selected earlier, and more often in a trial when using clarity to guide search than unique blur is when using blur to guide search. One potential explanation for this finding is that when participants fail to use blur or clarity to guide search, when instructed to do so, they would likely fall back on a similar search strategy as when no instructions are provided. When no instructions are provided, unique clarity is shown to capture attention, while unique blur repelled attention. This may be the reason that unique clarity was selected for to a higher degree than unique blur when both were task-relevant. It also suggests that when clarity is task-relevant, its attentional selection is greater than when blur is task-relevant.

Discussion

In Experiment 2, the primary research question investigated was whether resolution is a search asymmetry, and if there was evidence of a fixed or a reconfigurable resolution feature detector. The RT and eye movement results both supported that resolution is not a search asymmetry, but instead that resolution's influence on attention is contingent upon its task-relevance. This provides evidence for a reconfigurable resolution feature detector. The strongest support for this conclusion comes from the eye movement results. When unique blur was task-relevant through both the instructions and probability manipulations (unique blur occurred at target 67%), then blur was selected for, with the proportion of first fixations to a blurred singleton being well above chance. The fact that the blurred singleton was fixated first at a higher rate than chance helped explain how the blurred target condition had the fastest RT for the *Use Blur* task-relevance type. Both results supported that blur was used to guide attention. Previously, blur has been shown to be ignored, based on RT data, but also weakly repelling attention towards nearby clarity (or clarity, especially that close to blur, captured attention), based on Exp. 1 eye movement data. However, by making blur task-relevant, blur was used to guide selective attention towards it spatial location.

Critically important, if resolution was a search asymmetry, indicating a fixed resolution feature detector, then instructing participants to use blur should not have aided in finding the target. For example, Treisman and Souther (1985) had participants search for an O amongst Qs, which resulted in an inefficient search, even though the O was task-relevant. Unlike the O amongst Qs search asymmetry example, making blur task-relevant did produce faster reaction times to the blurred target singleton compared to when blur was task-irrelevant. However, the search times did not produce what would typically be thought of as 'pop out' or an efficient search because even though using blur was beneficial to find the target, it was not always the target.

Resolution's Attentional Guidance in Task-Relevance Types other than Use Blur

Experiment 2 replicated the first fixation to a singleton results of Experiment 1 with the *No Instructions* task-relevance type. This is important as it provides further confidence in the conclusion that when resolution is task-irrelevant unique clarity strongly captures attention, while unique blur weakly repels attention or clarity weakly captures attention to clear items nearby blur. Furthermore, the first fixation relative to a blurred singleton also replicated Exp. 1's finding that blur repels towards nearby clarity or clarity weakly captures attention to clear items nearby blur.

Unique clarity when task-relevant seems to facilitate search using unique clarity beyond what has been seen when resolution was task-irrelevant. This is very interesting, since an application for this line of research is to include it in computer software to direct users' attention on computer screens or heads-up displays by having critical regions in focus and the surrounding regions blurred. Perhaps, training to making unique clarity more task-relevant to the user may also make this software more effective in directing a user to a critical region.

The *Do Not Use Unique Blur or Clarity* task-relevance type resulted in the loss of the natural selective bias for unique clarity in terms of its RT speed advantage over blur. However, the eye movement results showed that unique clarity still captured attention and unique blur weakly repelled attention or clarity weakly captures attention to clear items nearby blur. Nevertheless, unique clarity did not appear to capture attention as strongly as the *No Instructions* task-relevance type, which indicates that instructions alone did have an influence on resolution's influence on attention. This was particularly evident from the very beginning of the practice trials, prior to the impact of training with the probability manipulation, as shown in Figure 21, and discussed in more depth in the next section.

Learning to Use Blur

The trial-by-trial analysis of fixating a blurred or clear singleton first showed that using blur to guide search resulted in learning to fixate blurred items more often as the experiment progressed. Blurred singletons were fixated above chance at the beginning of the experiment, but not nearly to the extent that unique clarity was fixated when participants were instructed to use clarity. In fact, by the end of the experimental session, participants instructed to use blur did not first fixate blurred singletons as often as participants instructed to use clarity starting the experiment first fixated clear singletons. This shows that there is a natural bias towards unique clarity. The main finding was that unique blur was used to guide search very early on, but there was room for improvement with continued use. An alternative explanation is that the participants were initially able to inhibit their response to clear items, which improved throughout the experimental session. Interestingly, there was a trend to inhibit fixating the clear singletons across trials in the *No Instructions* and *Do Not Use Unique Blur or Clarity* task-relevance types. Importantly, both of those two task-relevance types (*No Instructions* & *Do Not Use Unique Blur or Clarity*) had resolution singletons that were noninformative of the target's location. Therefore, the trend to inhibit fixations to clear singletons across trials suggests the participants learned that unique clarity was not as informative to find the target as they initially thought at the start of the experiment. Thus, over the course of the experiment, participants learned to inhibit responses to unique clarity and non-singleton blurred items.

No Difference in Time to First Fixate Task-Relevant Blurred and Clear Target Singletons

Does it take longer to start fixating a blurred target singleton when using blur to guide attention than a clear target singleton when using clarity to guide attention? The analysis of the time to fixate a target singleton showed that there was not a significant difference in the time to fixate a blurred or clear target singleton when the participant was searching for the same resolution (e.g., *Use Blur – Blurred Target Singleton*). This is again support that resolution is not a search asymmetry because both resolution target singletons were fixated at approximately the same time, when task-relevant. This is evidence of the existence of a reconfigurable resolution feature detector.

The Influence that Resolution First Fixated has on Reaction Time

The primary question in this analysis was how reaction time would be influenced by fixating a blurred or clear letter first between the *Use Blur* and *Use Clarity* Task-Relevance Types. The main take away from the conditionalized Log_{10} (RT) results is that there was additional support that resolution is not a search asymmetry. This is based on reaction times not significantly differing between the *Use Blur* and *Use Clarity* Task-Relevance Types when fixating the target singleton in the same resolution. Instead, this is support that resolution's guidance on attention is quite similar for blur and clarity when task-relevant. There was also an interesting finding that when the clear target singleton was fixated first produced faster reaction times than when the blurred target singleton was fixated first. There was evidence that the slower RT for when the blurred target singleton was fixated first was likely due to participants using clarity to guide attention and first fixating the blurred target singleton and continuing to search after having already fixated the target. Conversely, when participants were using blur to guide search and first fixated a clear target singleton, the participants were more often terminate search.

Average Number of Items Fixated to Find the Target

How many items are searched on average before finding a clear or blurred target in the All and Target Singleton conditions across the four Task-Relevant Types? Overall, the results for the average number of items searched supported that to a large degree unique clarity captured attention and unique blur repelled attention or clarity weakly captures attention to clear items nearby blur. However, unique blur was selected for when made task-relevant, as shown by having much fewer items fixated than the All Blur and Clear Target Singleton conditions. These results supported that resolution is not a search asymmetry, but contingent on resolution task-relevance.

Overall, Experiment 2's RT and eye movement analyses supported the hypothesis that resolution is not a search asymmetry; rather, resolution's influence on attention is contingent upon its task-relevance. These findings support the existence of a reconfigurable resolution feature detector. When resolution is task-relevant, both unique clarity and unique blur capture attention. When resolution is task-irrelevant, unique clarity captures attention, while unique blur weakly repels attention towards nearby clarity or clarity weakly captures attention to clear items nearby blur. The evidence from both the First Fixation to a Singleton and the Average Number of Items Searched results suggested that unique blur was not selected for as much as unique clarity when both were task-relevant. It may be that unique clarity is selected for to a greater degree than unique blur. But, these differences may also be due to participants not using the instructions to use blur or use clarity and instead falling back on a more default mode of search, which would be similar to the *No Instructions* Task-Relevant Type of search, which is naturally biased towards unique clarity. Therefore, in Experiment 3 a feature search will be used, which has participants only searching for a blurred item or only searching for a clear item. This should help keep participants focused on using a specific resolution because it will be task-relevant on every trial as opposed to in Experiment 2 where there was a probability trade-off. For example, participants using blur to guide search did have trials where the target was a clear singleton T. In Experiment 3, if instructed to determine the presence or absence of a blurred item, using blur to guide search will be needed on every trial and should result in continuing to use blur throughout such trials. Experiment 3 will be able to further investigate if resolution is a search asymmetry and because it is a feature search with different set sizes, RT x Set Size search slopes will be analyzed for evidence as to whether blur and/or clarity are processed preattentively or require attention.

Experiment 3: Are Blur and Clarity Preattentively Processed?

The aim of Experiment 3 was to provide additional support as to whether visual resolution is a search asymmetry, and if blur and clarity are processed preattentively, by having participants search specifically for a blurred or clear target. Across two conditions, participants searched for the presence of a blurred or clear target singleton, amongst distractors with the opposite resolution, while varying set size (2, 4, & 8). Participants were asked to determine if the task-relevant resolution target was present by responding Yes or No. This design allowed for set size to be manipulated as it has typically been used in studies of visual search, to provide evidence of efficient or inefficient search through analyzing RT x Set Size search slopes (Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989).

Preattentive versus Attention Required Hypotheses

Both blur and clarity will be investigated whether either or both are processed preattentively or require attention. The RT x Set Size search slopes will reveal if processing occurs preattentively or not, where a flat search slope < 10 msec/item will be support for preattentive processing and steeper slopes ~20-30 msec/item will be support for attention being required (Wolfe, 2007).

Search Asymmetry Hypotheses

If both blur and clear target present RT x Set Size search slopes are not significantly different from one another, then that would be evidence that resolution is not a search asymmetry. However, if one is steep with the other is flat, then that would be evidence that resolution is a search asymmetry (Treisman & Gormican, 1988; Treisman & Souther, 1985).

Method

Participants

Twenty-eight participants from Kansas State University were recruited from the Department of Psychological Sciences undergraduate research pool (17 males, *M* age = 19.14). Participants' vision was 20/30 or better, which was determined by using FrACT (Bach, 1996; Bach, 2007). All participants were naïve to the purpose of the experiment and were not participants in Experiments 1 or 2. Study procedures were approved by Kansas State University's Institutional Review Board, and all participants gave their informed consent prior to completing the study, for which they received class credit.

Apparatus and Stimuli

The same blurred and clear T letter stimuli used in Experiments 1 and 2 were presented, but at set sizes 2, 4, and 8 (Figure 26), with four rotations (0 upright, 90, 180, & 270) (Figure 27). Furthermore, the stimuli were shown on 17-inch Samsung SyncMaster 957 monitors set at a refresh rate of 85 Hz. Participants viewed the monitor at 53.34 cm using chin rests to stabilize the head to reduce motion during the experiment. The monitors had a resolution of 1024 x 768 pixels, and 37.8° x 28.7° of visual angle. The monitors were calibrated using a Spyder3Elite photometer, with a luminance maximum of 91.3 cd/m^2 and a minimum of 0.33 cd/m^2 with a gamma of 2.2. Responses were made using Cedrus model RB-834 response pads. The letters were shown on an imaginary circle, which had a radius of 9° of visual angle. The clear T stimuli's vertical and horizontal lines were both 44 pixels (1.65° of visual angle) in length and 4 pixels (0.15° of visual angle) in width. The set size of two presented letters from the top of the circle at the orientation locations of 90° and 270°. When the set size was four, the letters were shown from the top of the circle at the orientation location of 0, 90, 180, and 270. With a set size of eight, the letters were shown from the top of the circle at the orientation locations of 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°.

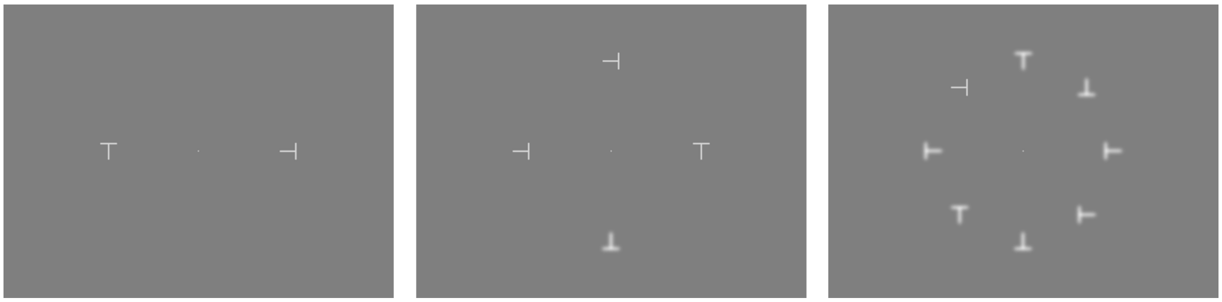

Figure 26. Set size of 2, 4, and 8 stimuli examples.

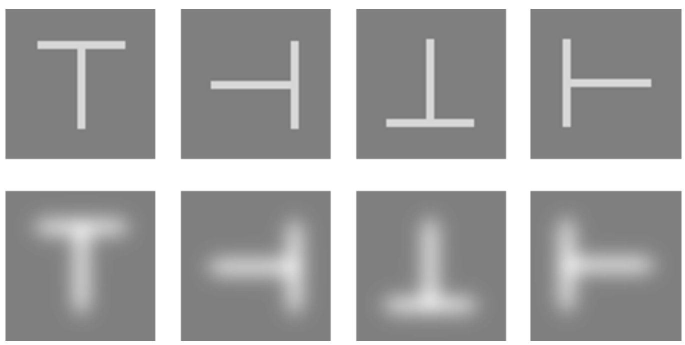

Figure 27. Image of clear and blurred T stimuli letter rotations. Row 1 clear T letters rotated (0, 90, 180, & 270). Row 2 blurred T letters rotated (0, 90, 180, & 270).

Design

A within-subjects design was used which was a 2 (*Target Resolution*: Blurred vs. Clear) x 2 (*Target Presence*: Present vs. Absent) x 3 (*Set Size*: 2, 4, & 8). The *Target Resolution* was blocked and the order counterbalanced for Blur versus Clear target resolutions. The target location was counterbalanced to occur equally often at all possible locations within each set size. The set sizes were randomized within each block. For example, the first block could have the participants detect the presence or absence of a blurred target singleton versus all clear (i.e., target absent) trials, while the second block had participants detect the presence or absence of a clear target singleton versus all blurred (i.e., target absent) trials. Each of the two blocks had 144 trials for a total of 288 trials. Within each of the blurred and clear blocks, the variables for *Target Presence* and *Set Size* were randomized, but they were equalized, such that that within a block of 144 trials there were 72 Target Present trials and 72 Target Absent Trials, there were also 48 trials for each of the set sizes 2, 4, and 8. When the target was present, the set size of 2 had 12 trials per target location (Left or Right), the set size of 4 had 6 trials per target location (Top, Right, Bottom, & Left), and the set size of 8 had 3 trials per target location (Top, Top-Right, Right, Bottom-Right, Bottom, Bottom-Left, Left, & Top-Left).

Procedure

A trial began with a fixation cross (63x63 pixels, 2.36° of visual angle) presented in the middle of the screen until a button was pressed to begin the trial. A gray screen with a small light gray dot (3x3 pixels, 0.11° of visual angle) in the middle of the screen was shown for 506 msec (43 retraces at 85 hertz). Stimuli were shown until a response was made. Participants needed to respond whether the target was present or absent by responding if the target resolution was present (Yes or No). The *Yes* button was on the right and *No* button was on the left for all participants. After responding, participants were given feedback by being visually shown the word *Correct* or *Incorrect* for 1 second. A gray screen followed a feedback response for 1 second.

Participants started with 96 practice trials, which had them switch the target resolution halfway through the practice trials. At the end of the practice trials, participants were given their cumulative accuracy score. Participants had three mandatory breaks for at least 10 seconds during the experimental trials, which occurred after 72 trials had been completed. The second break occurred before starting the second block when participants were instructed to find the target with the opposite resolution. During each break and at the very end of the experiment (288 trials), participants were give feedback on their cumulative accuracy. Participants were asked to write down their current cumulative accuracy on a score sheet at the end of each block, which was handed in to the experimenter at the end of the session. This task was added to increase participants effort when completing the experiment. At each break, participants were told which resolution the target was. At the end of the experiment, all participants were debriefed and thanked for their time.

Results

Cleaning Data

A total of 8064 trials were collected with a mean accuracy of 98%. The data was cleaned by removing all incorrect responses (123 trials). All the reaction times were within the > 150 msec and < 10 seconds filter used in the previous two experiments. Therefore, no trials were removed based on reaction time. Overall, there were 7941 trials for the following analyses.

Reaction Time Analyses

As with the Experiment 1 and 2 RT analyses, the following analyses were completed using the dependent measure of correct trial reaction times to determine the presence or absence of the target. The following analyses are all performed using Log_{10} (RT) to account for the non-normal distribution of the raw reaction time data. Figure 28 shows the mean Log_{10} (RT) in msec and ± 1 SEM for *Target Resolution x Target Presence x Set Size* with the untransformed reaction time (RT*) as a secondary y-axis. A linear multilevel model with effect coding was performed in JMP Pro 12. The model included Log_{10} (RT) as the dependent measure, *Target Resolution*, *Target Presence*, and *Set Size* were included as three main effects, three two-way interactions, and one three-way interaction. Additionally, *Log_{10} (Trial)* was included as a main effect. The random effects structure included the main effects and interaction for *Target Resolution x Target Presence x Set Size*, and the main effect of *Log_{10} (Trial)* across participants with adjusted R^2 = .29, RMSE = 0.12. Table 31 provides the model's parameter estimates.

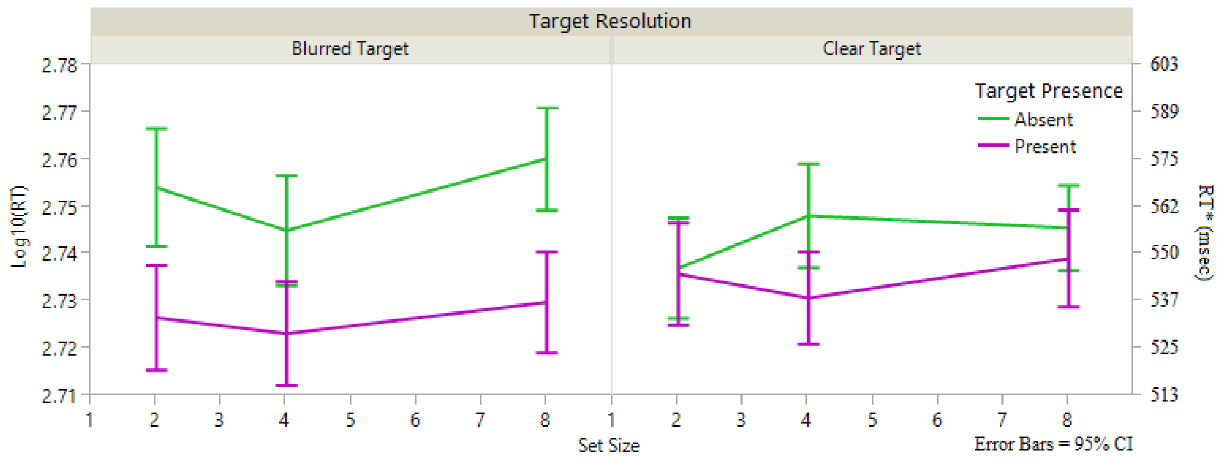

Figure 28. Log_{10} (RT) *M* for *Target Resolution x Target Presence x Set Size* with 95% CI bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale.

Table 31

Parameter Estimates for Log_{10} (RT) Target Resolution x Target Presence x Set Size Linear Multilevel Model

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	2.786	0.026	42.11	106.32	<.001
TR(B)	0.002	0.005	26.00	0.52	0.607
SS	0.001	0.001	27.05	1.48	0.151
TR(B)*(SS-4.67019)	-1.8E-05	0.001	26.59	-0.03	0.977
TP(A)	0.009	0.003	26.99	2.85	0.008
TR(B)*TP(A)	0.005	0.002	26.95	2.40	0.024
(SS-4.67019)*TP(A)	3.8E-04	0.001	27.07	0.58	0.569
TR(B)*(SS-4.67019)*TP(A)	1.3E-04	4.6E-04	27.25	0.28	0.781
Log_{10} (Trial)	-0.025	0.011	25.57	-2.24	0.034

Note. Target Resolution = TR. Blurred = B. Set Size = SS. Target Presence = TP. Absent = A. Model was performed using effect coding [(TR: Blurred = +1, Clear = -1); (TP: Absent = +1, Present = -1)]. Set Size was mean centered. dfDen = degrees of freedom used in the denominator. Std Error = Standard Error.

Table 32 showed the mean Log_{10} (RT) with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for *Target Resolution x Target Presence x Set Size*. The results show that there was a significant main effect for *Log_{10} (Trial)*, $F(1, 25.6) = -2.24$, $p < .034$, indicating that participants began to respond faster as they progressed through the experiment. There was also a significant main effect for *Target Presence*, $F(1, 27) = 2.85$, $p < .008$, which is the normal effect such that RT was greater for absent trials. There was also a significant interaction between *Target Resolution x Target Presence*, $F(1, 27) = 2.40$, $p < .024$. This interaction was further investigated with a Tukey HSD test (see Table 33), which found that the response to the Blurred Target Absent condition was significantly longer than the Blurred Present condition, while both Clear Present and Absent conditions did not significantly differ from one another but did trend with the same pattern of results as the Blur conditions. No other main effects or interactions were significant. Most importantly, there was neither a significant main effect for *Set Size* nor for *Target Resolution*, nor was there a significant interaction between these factors. As shown in Figure 28 and Table 33, neither blur nor clear target resolutions significantly varied across set size, nor from each other, which supported that blur and clarity are processed preattentively and resolution is not a search asymmetry. Evidence that blur and clarity are processed preattentively comes from the results that both blur (1.01 msec/item [search slopes untransformed from Log_{10} (RT) = 2.728 msec/item]) and clear (1.01 msec/item [search slopes untransformed from Log_{10} (RT) = 2.733 msec/item]) target present conditions' RT x Set Size search slopes are flat. Furthermore, target search across resolutions was not a search asymmetry based on both target resolution RT x Set Sizes search slopes, which were flat and did not significantly differ from one another. This suggests the existence of a reconfigurable resolution feature detector, instead of a fixed resolution feature detector that is selective for clarity.

Table 32

Target Resolution x Target Presence x Set Size: Log10 (RT) M with SD and RT GM with GSDs*

TR	TP	SS	Log_{10} (RT) M	Log_{10} (RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
Blurred	Absent	2	2.755	0.130	569	422	767
Blurred	Present	2	2.727	0.124	534	401	710
Blurred	Absent	4	2.745	0.122	556	421	736
Blurred	Present	4	2.724	0.117	529	404	694
Blurred	Absent	8	2.760	0.113	576	444	746
Blurred	Present	8	2.730	0.117	537	410	704
Clear	Absent	2	2.736	0.114	545	419	708
Clear	Present	2	2.735	0.112	543	419	704
Clear	Absent	4	2.748	0.119	559	426	735
Clear	Present	4	2.731	0.105	538	423	684
Clear	Absent	8	2.746	0.098	557	445	697
Clear	Present	8	2.740	0.115	549	422	716

Note. Target Resolution = TR. Target Presence = TP. Set Size = SS. RT* = Untransformed Reaction Time. M = Marginal Means. GM = Geometric Mean. SD = Within-subject Standard Deviation. GSD = Geometric within-subject Standard Deviation. RT* has asymmetrical -1 and +1 GSDs because of the positive skew of the RT data when untransformed.

Table 33

Tukey HSD Comparisons: Target Resolution x Target Presence

TR	TP	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Blurred	Absent	A	2.756	0.014	2.727	2.785
Clear	Absent	AB	2.742	0.014	2.713	2.770
Clear	Present	AB	2.733	0.014	2.705	2.762
Blurred	Present	B	2.728	0.014	2.700	2.757

Note. Target Resolution = TR. Target Presence = TP. Levels not connected by same letter are significantly different ($\alpha = 0.05$, $Q = 3.92$). Sq = Squares. Std Error = Standard Error.

Discussion

In Experiment 3, the two main research questions were whether resolution is a search asymmetry, and whether blur and/or clarity are processed preattentively or require attention. Strong evidence from the RT x Set Size search slopes supported that resolution is not a search asymmetry and that both blur and clarity are processed preattentively, which theoretically, support the existence of a reconfigurable resolution feature detector. The RT x Set Size search slopes for both blur and clear target present trials were ~1 msec/item each. Both RT x Set Size search slopes are extremely small, which support that resolution is not a search asymmetry because the slopes did not significantly differ from one another, and both blur and clarity are processed preattentively because the slopes are far less than 10 msec/item.

These results together with those of Loschky et al.'s (2014) support the hypothesis that blur is processed preattentively. The current study used comparison of search slopes in visual search, while Loschky et al. used comparison of detection rates with or without dual-task load. VanRullen, Reddy, and Koch (2004) discussed and provided evidence of two independent dimensions of attentional resources for visual search versus dual-task performance. The first dimension of attentional resources is preattentive$_{vs}$ – attention$_{vs}$ (vs = visual search). Preattentive$_{vs}$ allows visuals search task to be processed in parallel, while attention$_{vs}$ requires serial processing. The second dimension of attention resources is preattentive$_{dt}$ - attention$_{dt}$ (dt = dual-task). Preattentive$_{dt}$ has visuals search task that are part of a dual-task paradigm processed in parallel, while attention$_{dt}$ requires visual search tasks, that are part of a dual-task paradigm to be serially processed. For example, discriminating a rotated L amongst rotated + distractors will 'pop out,' suggesting it was processed in parallel when performed as a single visual search task. However, when the same task is accompanied by an additional task in a dual-task paradigm, such as identifying whether all the letters in the center of the screen are identical, then performance on the rotated L versus +s decreases. VanRullen et al. claim that this is evidence that discrimination for the rotated L versus +s task required attention$_{dt}$. Parallel processing does not mean that the task can be performed without attention. However, orientation and color discrimination tasks have be shown to be processed preattentively, even when part of a dual-task paradigm, which supports that these discriminations are preformed with preattentive$_{dt}$. VanRullen et al. put forth a Decision Tree (p. 10), that predicts where processing for the target and distractors may be located in the brain, by using the preattetnive$_{vs}$ – attention$_{vs}$ and preattetnive$_{dt}$ – attention$_{dt}$ dimensions. Experiment 3's results provide strong evidence that blur and clarity were processed with preattetnive$_{vs}$. Loschky et al. (2014) showed that blur detection was processed with preattentive$_{dt}$. Therefore, based on VanRullen et al.'s Decision Tree, blur and clarity should have a specific population of cells that processes blur and clear information in a lower cortical area. Where exactly blur is processed is currently unknown. However, blur and clarity seem very likely to be processed where binocular cells are present because Kompaniez, Sawides, Marcos, and Webster (2013) have shown interocular transfer of blur adaption. Therefore, the special population of cells that process blur and clarity should be located somewhere that binocular cells exist in a lower cortical area, possible as early as V1.

Chapter 4 - General Discussion

The current study provides evidence that visual resolution is not a search asymmetry, but instead that the influence of resolution on attention is contingent upon its task-relevance. This suggests the existence of a reconfigurable resolution feature detector. When resolution is task-irrelevant, unique clarity strongly captures attention, while unique blur appears to weakly repel attention towards nearby clarity (or clarity, especially that close to blur, captured attention). When resolution is task-relevant, both unique blur and clarity capture selective attention to their spatial location. Furthermore, RT x Set Size search slope evidence supported that both blur and clarity are processed preattentively.

Experiment 1 extended the methodology from Peterson (2016) by incorporating eye tracking, which allowed for the additional eye movement measures. Importantly, it was the eye movement analyses that revealed evidence that unique blur appeared to repel attention towards nearby clarity (or clarity, especially that close to blur, captured attention). This result contrasts with the experiment's RT results which suggested that blur is ignored by selective attention. The eye movement results are also in contrast with earlier RT results from Peterson (2016) and eye movement results from Enns and MacDonald (2013; Exp. 3), which both suggested that blur is ignored by selective attention. However, the increased control from Peterson's (2016) visual search methodology and the inclusion of more sensitive measures of resolution's influence on attention with the eye movement measures, at present, it is undecidable whether blur weakly repelled attention to nearby clarity, or clarity weakly captures attention to clear items nearby blur. However, as discussed earlier in Exp. 1's Discussion section, there are reasons to think that blur is repelling attention towards nearby clarity based on what is known about visual discomfort, visual accommodation, neural suppression and/or inhibitory processes.

A combination of results from several different analyses all point toward blur weakly repelling towards nearby clarity (or clarity, especially that close to blur, captured attention). The first fixation to a singleton data revealed that blurred singletons are fixated as the first letter during search less often than chance, which was evidence that unique blur repels attention (or all clarity captures attention). The blurred singleton condition was further analyzed by finding that the clear letters adjacent to the blurred singleton were fixated above chance, while the other clear letters in the display were either at or below chance, which provides evidence that blur repels attention *towards nearby clarity* (or clarity, especially that close to blur, captured attention). Additional support comes from the item order that blurred target singletons were searched in. Blurred target singletons were searched more often as the last (or second to last) item in the set size than a blurred target in the All Blurred condition. Also, blurred target singletons were less often searched as the first item than a blurred target in the All Blurred condition. These two findings based on the item order results strongly suggest that blur is repelling attention and that blur does not only repel attention at the onset of the stimuli, but persistently repels attention throughout the trial until there is no other option but to search the blurred item (or clarity, especially that close to blur, captured attention).

As discussed in Experiment 1's Discussion section, an alternative interpretation of Experiment 1's results was that all clarity captures and clear letters adjacent to a blurred singleton create a unique degree of arc that heightens those specific clear letters' salience by making them the strongest local signal of clarity. As argued earlier, results for the first letter fixated relative to the blurred singleton and blurred target item order provided evidence against the *All Clarity Captures* and the *Strongest Local Signal of Clarity Captures* hypotheses. Instead, the results are best explained by the *Blur Repels Towards Nearby Clarity* hypothesis. The *All Clarity Captures* and the *Strongest Local Signal of Clarity Captures* hypotheses were then merged to create the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis. Three saliency models were compared in an unsuccessful attempt to differentiate the *Blur Repels Towards Nearby Clarity* versus the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses. Three saliency models (GBVS, AWS, & WMAP), two of which (GBVS & AWS) were rated as among the best available (Borji et al., 2013), were ran on example stimulus arrays through the saliency models for the All Blurred, All Clear, Blurred Target Singleton, and Clear Target Singleton conditions producing saliency maps. The saliency models' results were inconclusive as each model made different predictions. WMAP performed the best compared to the eye movement results from Experiment 1 predicting that unique clarity would be selected for, while unique blur would not be selected for, but adjacent clear letters were selected for. Importantly, however, the results of Experiments 2 and 3 for when blur was task relevant produced results consistent with the GBVS and AWS saliency models, namely capture by blur. Thus, the saliency models' results suggest that a researcher could find different saliency models that would generate saliency maps congruent with their behavioral results under different conditions (e.g., blur is task-relevant vs. -irrelevant), but neither saliency models in general, nor any specific saliency model in particular reliably predict unique resolution saliency that is congruent with the full range of behavioral results in the current dissertation.

An additional issue with using saliency models is that they could not differentiate between the two competing alternative hypotheses: *Blur Repels Towards Nearby Clarity* versus *Strongest Local Signal of Clarity, then All Other Clarity Captures*. As shown by the quantitative models for average number of items fixated for each *Resolution x Condition* showed, both hypotheses made the same predictions. The *Blur Repels Towards Nearby Clarity* versus *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses make identical average number of items searched predictions, which would also result in identical saliency maps throughout a search for each *Resolution x Condition* combination, yet the reason behind these predictions differ. For example, for a blurred target singleton condition, both hypotheses predict attentional capture to the clear letters adjacent to the blurred target singleton, while reducing the blurred target singleton's salience. The *Blur Repels Towards Nearby Clarity* hypothesis explains the prediction by blur actively repelled attention towards nearby clarity, but the *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis explains this prediction based on a heightened salience level for the clear letters adjacent to the blurred singleton forming a unique degree of arc. Importantly, both hypotheses predict the blurred target singleton would be the last item searched because blur is repelling attention until there is no other clear letter option (*Blur Repels Towards Nearby Clarity* hypothesis) or blur is passively fixated at the end of the search after all the clear letters that captured attention were not the target (*Strongest Local Signal of Clarity, then All Other Clarity Captures* hypothesis).

How could the *Blur Repels Towards Nearby Clarity* versus *Strongest Local Signal of Clarity, then All Other Clarity Captures* hypotheses be differentiated? Three possible future experiments were fully discussed in Experiment 1's Discussion section, 1) Blank Space Experiment, 2) EEG experiment testing for distractor positivity component in ERP wave, and 3) Measuring activity in the lateral intraparietal area when shown blurred and clear stimuli.

The purpose of Experiment 2 was to investigate whether visual resolution was a search asymmetry. Previously, Peterson's (2016) RT evidence suggested that unique clarity could be used to guide search, while unique blur was ignored by selective attention when resolution was task-irrelevant. To determine whether visual resolution was a search asymmetry, Exp. 2 made resolution task-relevant, by having participants either use blur, use clarity, not use unique blur or clarity, or to do the search task without any instructions related to resolution, when determining the orientation of the target T. In addition to being given instructions, there was also a probability manipulation such that the task-relevant resolution when unique and present occurred at the target 67% of the trials, while the other resolution when unique and present occurred at the target on ~17% of the trials (i.e., at chance). The critical finding was that resolution is not a search asymmetry, but instead resolution's influence on attention is contingent upon its task-relevance. This suggested the existence of a reconfigurable resolution feature detector.

The strongest support for resolution not being a search asymmetry, but instead contingent upon task-relevance is drawn from the *Use Blur* task-relevance type's eye movement and RT results. The eye movement results showed that blurred singletons were the first letter fixated well above chance, indicating that blur was being selected for. The RT evidence showed that the blurred target condition had the fastest RTs compared to any other condition, again when blur was task-relevant. This only occurred in the *Use Blur* task-relevance type; all other task-relevance types as well as the results from Exp. 1 have resulted in the blurred target condition's RT not being significantly different from the all-blurred condition. The unique blur RT results have previously supported that blur is ignored by selective attention, but unique blur had previously only been task-irrelevant. By making blur task-relevant, it was used to guide attention to its spatial location. This finding is in line with Enns and MacDonald's (2013), finding that unique blur can draw attention when it is task-relevant. Importantly, this result also means that searching for a blurred target when blur is task-relevant is not like searching for an O amongst Qs. Therefore, it seems that searching for blur is not a search for the lack of a critical feature, in this case the lack of higher spatial frequencies. Instead, blur may be processed as a basic feature that can be detected and selected for by directing attention to its spatial location. This finding is congruent with Loschky et al.'s (2014) dual-task evidence suggesting that blur is processed preattentively.

Additional evidence that resolution is not a search asymmetry came from the Time to Fixate a Singleton Target results. There was no significant difference in the time it took to fixate the blurred or clear target singleton as the first item when participants used the same resolution as the target to guide search. This finding is very important as is suggests that there is not a strong difference between processing speed and deployment of attentional selection to a unique blur or clear singleton when task-relevant. Thus, this is evidence that blur and clarity are simply points on a continuum of resolution, which is all processed at the same speed. Also, conditionalized Log_{10} (RT) results provided evidence that resolution is not a search asymmetry based on reaction times not significantly differing between the *Use Blur* and *Use Clarity* Task-Relevance Types when the target singleton in the same resolution was first fixated during search. The average number of items searched to find the target data also supports that resolution is not a search asymmetry. The average number of items searched to find the target was significantly less in the *Use Blur* Task-Relevance Type for blurred target singletons than clear target singletons, showing that, when blur is made task relevant, it can produce more efficient search than task-irrelevant clarity. Together, providing evidence of the existence of a reconfigurable resolution feature detector.

Participants instructed to use blur were able to do so at the start of the experiment. There was also evidence of a learning component found because there was still significant improvement in the use of blur to guide attention as the experiment progressed. This was shown by participants instructed to use blur fixating blurred singletons as the first item in a trial more often as the experiment progressed. There was also an upward trend to fixate a clear singleton first in the *Use Clarity* Task-Relevant Type. However, it was not as significant of an increase, because the probability of fixating a clear singleton at the start of the experiment was already higher than the probability of fixating blurred singletons in the *Use Blur* Task-Relevance Type by the end of the experiment, when learning had slightly occurred. Also, the *No Instructions* and *Do Not Use Unique Blur or Clarity* Task-Relevance Types showed a downward trend to fixate unique clarity less as the experiment progressed.

Experiment 3 continued to investigate whether visual resolution is a search asymmetry, and also whether blur and clarity are processed preattentively. A feature search was used with blurred and clear target resolutions, which were blocked and counterbalanced. Participants searched for the presence of a blurred or clear target singleton, amongst distractors with the opposite resolution, while varying set size between 2, 4, and 8. Participants determined if the task-relevant resolution target was present (Yes or No). RT x Set Size search slopes were flat for both blur and clear target present trials, which provided strong evidence that both blur and clarity are processed preattentively. Interestingly, the blurred target present condition (Blurred Target Singleton) was significantly faster than the blurred target absent condition (All Clear), while the clear target present (Clear Target Singleton) and absent (All Blurred) conditions did not significantly differ. This finding shows that there was a greater range in time needed to determine whether a blurred target singleton is present or absent compared to whether a clear target singleton is present or absent. Why such a difference emerged is not entirely obvious. A possible explanation is that when the target is defined by a specific resolution (Clear or Blurred), then a group of blurred items stands out as All Blurred more than a group of clear items stands out as All Clear. Perhaps that is because clear is the perceptual default condition, but blurred is treated as perceptually aberrant (because we tend to want to avoid it). However, when blur is the target resolution, then clarity may not be treated as perceptually aberrant, which results in more time needed to determine the lack of blur in the All Clear condition. An additional finding, based on both RT x Set Size search slopes not significantly differing from one another was further evidence that resolution is not a search asymmetry. Instead, it provided that blur and clarity can be used to guide attention when task-relevant, which supports the existence of a reconfigurable resolution feature detector.

Experiment 3 is strong evidence that both unique blur and clarity are processed preattentively. Loschky et al. (2014) have previously shown evidence that blur is processed preattentively based on the fact that blur detection was unaffected by cognitive load. VanRullen et al. (2004) describe in their Decision Tree (p. 10), that features that are processed using both preattentive_{vs} and preattentive_{dt} have special neuronal populations in lower cortical areas. Kompaniez et al. (2013) have shown interocular transfer of blur adaption, which implies that blur is processed in binocular cells. Therefore, it is possible that blur and clarity are processed as early as V1. Much like other preattentive features processed in V1 that show perceptual aftereffects such as the tilt aftereffect or spatial frequency aftereffect, blur adaptation shows aftereffects in the direction opposite of the resolution adapted to (Webster et al., 2002). This is support blur and clarity form a featural dimension and may have cells selectively tuned for a continuum with opposite ends that are responsive to lower resolution (blur) and higher resolution (clarity).

By increasing our understanding of how resolution guides attention, and how it does so under different conditions, we can then potentially use it to make search more efficient. For example, a heads-up display or a computer screen could potentially quickly direct a user's attention to important information by blurring most of the display and keeping the critical region clear. But, if so, important questions remain about how much blur is needed and how long must the blur be present. And similar to the goal of film makers, can using blur to guide viewers' attention be done without their awareness? Furthermore, Experiment 2 found that making clarity task-relevant facilitated guidance of unique clarity. Perhaps, it is possible to train users to direct attention with clarity to become even more efficient at guiding attention using resolution contrast.

Conclusion

The current study investigated resolution's influences on selective attention when task-relevant versus -irrelevant, if resolution is a search asymmetry or not, and if both blur and clarity are processed preattentively. Three experiments investigated these research questions by using a rotated L and T visual search paradigm (Exp. 3 used only T stimuli for Feature Search), where resolution was manipulated to be task-relevant or -irrelevant. The general conclusion is that both blur and clarity are processed preattentively and resolution is not a true search asymmetry, which supported the existence of a reconfigurable resolution feature detector. Importantly, to understand how visual resolution will influence selective attention, one must know whether resolution is relevant to the task at hand. Visual resolution has a dynamic relationship with selective attention such that when it is task-relevant both unique blur and unique clarity will capture attention. However, when task-irrelevant, unique clarity can capture attention, while unique blur appears to weakly repel attention towards nearby clarity.

References

Adeli, H., Vitu, F., & Zelinsky, G. J. (2017). A model of the superior colliculus predicts fixation locations during scene viewing and visual search. *Journal of Neuroscience*, *37*(6), 1453-1467.

Bach, M. (1996). The Freiburg visual acuity test—Automatic measurement of visual acuity. *Optometry and Vision Science, 73*, 49-53.

Bach, M. (2007). The Freiburg visual acuity test-variability unchanged by post-hoc re-analysis. *Graefe's Archive for Clinical and Experimental Ophthalmology, 245*, 965-971.

Borji, A., Sihite, D. N., & Itti, L. (2013). Quantitative analysis of human-model agreement in visual saliency modeling: A comparative study. *IEEE Transactions on Image Processing, 22(*1), 55-69.

Bouma, H. (1970). Interaction effects in parafoveal letter recognition. *Nature, 226*, 177-178.

Braun, J. (1994). Visual search among items of different salience: Removal of visual attention mimics a lesion in extrastriate area V4. *The Journal of Neuroscience, 14*(2), 554-567.

Campbell, F. W., & Westheimer, G. (1960). Dynamics of accommodation responses of the human eye. *Journal of Physiology, 151*, 285-295.

Ciuffreda, K. J., Wang, B., & Vasudevan, B. (2007). Conceptual model of human blur perception. *Vision Research, 47*(9), 1245-1252.

Egeth, H., & Dagenbach, D. (1991). Parallel versus serial processing in visual search: Further evidence from subadditive effects of visual quality. *Journal of Experimental Psychology, 17*, 551-560.

Enns, J. T., & MacDonald, S. C. (2013). The role of clarity and blur in guiding visual attention in photographs. *Journal of Experimental Psychology: Human Perception and Performance, 39*(2), 568-578.

Garcia-Diaz, A., Fdez-Vidal, X. R., Pardo, X. M., & Dosil, R. (2012). Saliency from hierarchical adaptation through decorrelation and variance normalization. *Image and Vision Computing, 30*, 51-64.

Garcia-Diaz, Leborán, V., Fdez-Vidal, X. R., & Pardo, X. M. (2012). On the relationship between optical variability, visual saliency, and eye fixations: A computational approach. *Journal of Vision, 12*(6), 1-22.

Gaspelin, N., Leonard, C. J., & Luck, S. J. (2017). Suppression of overt attentional capture by salient-but-irrelevant color singletons. *Attention, Perception, & Psychophysics, 79*(1), 45-62.

Harel, J., Koch, C., & Perona, P. (2007). Graph-based visual saliency. In *Advances in neural information processing systems* (pp. 545-552).

Held, R. T., Cooper, E. A., & Banks, M. S. (2012). Blur and disparity are complementary cues to depth. *Current Biology*, *22*(5), 426-431.

Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews Neuroscience, 2*(3), 194-204.

Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on pattern analysis and machine intelligence, 20(*11), 1254-1259.

Jiang, Y., & Chun, M. M. (2001). Selective attention modulates implicit learning. *The Quarterly Journal of Experimental Psychology*, *54*, 1105-1124.

Julesz, B., & Bergen, J. R. (1983). Human factors and behavioral science: Textons, the fundamental elements in preattentive vision and perception of textures. *The Bell System Technical Journal, 62*, 1619-1645.

Juricevic, I., Land, L., Wilkins, A., & Webster, M. A. (2010). Visual discomfort and natural image statistics. *Perception, 39*, 884-899.

Kompaniez, E., Sawides, L., Marcos, S., & Webster, M. A. (2013). Adaptation to interocular differences in blur. *Journal of Vision, 13*(6), 1-14.

Kosara, R., Miksch, S., Hauser, H., Schrammel, J., Giller, V., & Tscheligi, M. (2002). Useful properties of semantic depth of field for better F+C visualization. *Proceedings of the Joint Eurographics—IEEE TCVG Symposium on Visualization (VisSym),* 205-210.

López-García, F., Fdez-Vidal, X. R., Pardo, X. M., & Dosil, R. (2011). Scene recognition through visual attention and image features: A comparison between sift and surf approaches. In *Object Recognition*. InTech.

Loschky, L. C., & McConkie, G. W. (2002). Investigating spatial vision and dynamic attentional selection using a gaze-contingent multiresolutional display. *Journal of Experimental Psychology: Applied*, *8*, 99-117.

Loschky, L. C., McConkie, G. W., Yang, J., & Miller, M. E. (2005). The limits of visual resolution in natural scene viewing. *Visual Cognition, 12*(6), 1057-1092.

Loschky, L. C., Ringer, R. V., Johnson, A. P., Larson, A. M., Neider, M., & Kramer, A. F. (2014). Blur detection is unaffected by cognitive load. *Visual Cognition*, *22*(3-4), 522-547.

Malik, J., & Perona, P. (1990). Preattentive texture discrimination with early vision mechanisms. *JOSA A*, *7*(5), 923-932.

Mirpour, K., Arcizet, F., Ong, W. S., & Bisley, J. W. (2009). Been there, seen that: A neural mechanism for performing efficient visual search. *Journal of Neurophysiology*, *102*(6), 3481-3491.

O'Hare, L., & Hibbard, P. B. (2013). Visual discomfort and blur. *Journal of Vision, 13*(5), 1-12.

Olmsted, J. M. D. (1944). The role of the autonomic nervous system in accommodation for far and near vision. *The Journal of Nervous and Mental Disease, 99*(5), 794-798.

Peterson, J. J. (2016). *The effect of blur on visual selective attention* (Master's thesis, Kansas State University).

Phillips, S. & Stark, L. (1977). Blur: A sufficient accommodative stimulus. *Documenta Ophthalmologica*, *43*(1), 65-89.

Sawaki, R., & Luck, S. J. (2010). Capture versus suppression of attention by salient singletons: Electrophysiological evidence for an automatic attend-to-me signal. *Attention, Perception, & Psychophysics*, *72*(6), 1455-1470.

Smith, W. S., & Tadmor, Y. (2012). Nonblurred regions show priority for gaze direction over spatial blur. *The Quarterly Journal of Experimental Psychology*, *66*, 927-945.

Strasburger, H., Rentschler, I., & Jüttner, M. (2011). Peripheral vision and pattern recognition: A review. *Journal of Vision, 11*(5), 1-82.

Toates, F. M. (1972). Accommodation function of the human eye. *Physiological Reviews, 52*(4), 828-863.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive*

Treisman, A. & Gormican, S. (1988). Feature analysis in early vision: Evidence from search asymmetries. *Psychological Review, 95*(1), 15-48.

Treisman, A., & Souther, J. (1985). Search asymmetry: A diagnostic for preattentive processing of separable features. *Journal of Experimental Psychology: General*, *114*(3), 285-310.

Veas, E., Mendez, E., Feiner, S., & Schmalsteig, D. (2011, May). *Directing attention and influencing memory with visual saliency modulation*. CHI 2011, May 7–12, Vancouver, BC, Canada. Proceedings of the 2011 annual conference on human factors in computing systems, ACM, New York, NY.

VanRullen, R., Reddy, L., & Koch, C. (2004). Visual search and dual tasks reveal two distinct attentional resources. *Journal of Cognitive Neuroscience*, *16*, 4-14.

Webster, M. A., Georgeson, M. A., & Webster, S. M. (2002). Neural adjustments to image blur. *Nature Neuroscience, 5*(9), 839-840.

Wolfe, J. M. (2001). Asymmetries in visual search: An introduction. *Perception & Psychophysics, 63*(3), 381-389.

Wolfe, J. M. (2007). Guided search 4.0 current progress with a model of visual search. *Integrated Models of Cognitive Systems,* 99-119.

Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided search: An alternative to the feature integration model for visual search. *Journal of Experimental Psychology: Human Perception and Performance, 15,* 419-433.

Yantis, S., & Egeth, H. E. (1999). On the distinction between visual salience and stimulus-driven attentional capture. *Journal of Experimental Psychology: Human Perception and Performance, 25*, 661-676.

Appendix A - Set Size of 6: Average Number of Items Search for Resolution x Condition Probability Calculations

Table 34

Random Search Set

Item	Probability of each item being searched	Probability with Set Size 6	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 5/6)	0.833
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 5/6 * 4/5)	0.667
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 5/6 * 4/5 * 3/4)	0.500
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 5/6 * 4/5 * 3/4 * 2/3)	0.333
6	P(IS6) = P(IS6 | IS1D * IS2D * IS3D * IS4D * IS5D)	P(IS6) = P(1 | 5/6 * 4/5 * 3/4 * 2/3 * 1/2)	0.167

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D).

Table 35

Capture Search Set

Item	Probability of each item being searched	Probability with Set Size 6	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 1)	1
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 1 * 4/5)	0.8
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 1 * 4/5 * 3/4)	0.6
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 1 * 4/5 * 3/4 * 2/3)	0.4
6	P(IS6) = P(IS6 | IS1D * IS2D * IS3D * IS4D * IS5D)	P(IS6) = P(1 | 1 * 4/5 * 3/4 * 2/3 * 1/2)	0.2

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D).

Table 36

Repel Target Search Set

Item	Probability of each item being searched	Probability with Set Size 6	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 1)	1
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 1 * 1)	1
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 1 * 1 * 1)	1
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 1 * 1 * 1 * 1)	1
6	P(IS6) = P(IS6 | IS1D * IS2D * IS3D * IS4D * IS5D)	P(IS6) = P(1 | 1 * 1 * 1 * 1 * 1)	1

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D).

Table 37

Repel Distractor Search Set

Item	Probability of each item being searched	Probability with Set Size 6	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 4/5)	0.8
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 4/5 * 3/4)	0.6
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 4/5 * 3/4 * 2/3)	0.4
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 4/5 * 3/4 * 2/3 * 1/2)	0.2

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D).

Appendix B - Conditionalizing Time to Fixate a Singleton Target for First Fixated Letter's Resolution x Task-Relevance

How long did it take to fixate a blurred or clear target singleton when task-relevant or when it was the opposite resolution of what was task-relevant (e.g., fixated the blurred target singleton, when participants were supposed to use clarity to guide search). To investigate this research question, the time from the onset of the letters to when the first letter was fixated, specifically, when the blurred or clear target singleton was fixated first in the *Use Blur* and *Use Clarity* task-relevance types. Only the target singleton conditions were included because fixating the target was needed to correctly complete the task, whereas distractor conditions did not require fixating a singleton to complete the task. The data was cleaned with the same technique as explained when Time to Fixate a Singleton Target investigated only the blurred target singleton being fixated first when participants were using blur to guide search and the clear target singleton being fixated first when participants were using clarity to guide search.

A linear multilevel model with effect coding was performed in JMP Pro 12. The model included Time to Fixate a Singleton Target as the dependent measure, which was the time it took to fixate a target singleton, when it was the first letter searched, from the time when all the letters were displayed. Figure 29 shows the mean Time to Fixate a Singleton Target in msec and ± 95% CI for *Task-Relevance Type x Target Resolution x Resolution First Fixated*. The independent variables were effect coded: *Task-Relevance Type* (*Use Blur* = +1, *Use Clarity* -1), *Target Resolution* (Blur = +1, Clarity -1), and *Resolution Fixated First* (Blur = +1, Clarity = -1), which were included as three main effects, three two-way interactions, and one three-way interaction. Additionally, $Log_{10}(Trial)$ was included as a main effect. The random effects structure included the main effects and interaction for *Task-Relevance Type x Target Resolution x Resolution First Fixated* and the main effect of $Log_{10}(Trial)$ across participants with adjusted R^2 = .42, RMSE = 110. Table 38 provides the model's parameter estimates.

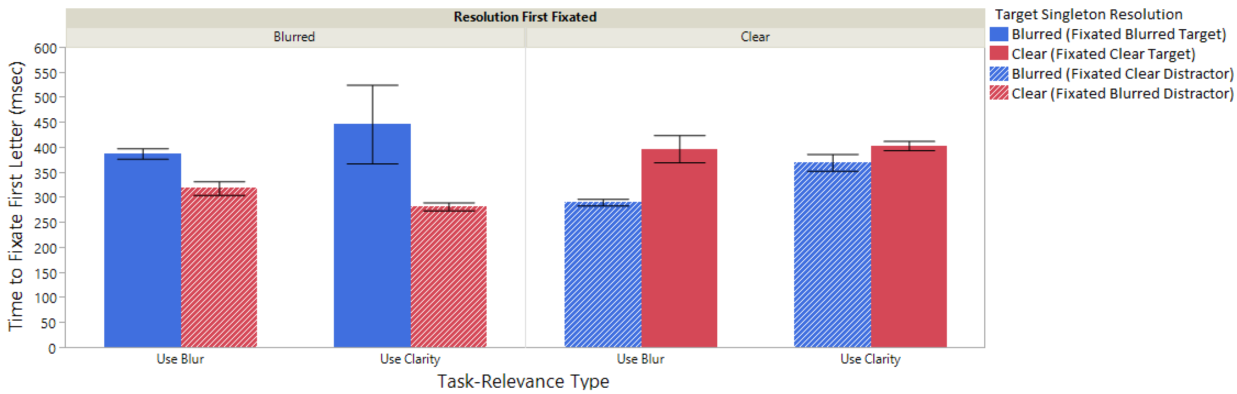

Figure 29. The mean Time to Fixated Singleton Target for *Task-Relevance Type x Target Resolution x Resolution First Fixated* with +/- 95% CI bars. Blurred Target Singleton condition has blue bars (Solid Blue Bars = Blurred Target Singleton was fixated first; Striped Blue Bars = Clear Distractor Nonsingleton letter was fixated first). Clear Target Singleton condition has red bars (Solid Red Bars = Clear Target Singleton was fixated first; Striped Clear Bars = Blurred Distractor Nonsingleton letter was fixated first).

Table 38

Parameter Estimates for Log_{10} (RT) Task-Relevance Type x Target Resolution x Resolution First Fixated Linear Multilevel Model

Fixed Effects	Estimates	Std Error	dfDen	t Ratio	p-value
Intercept	401.543	22.634	68.81	17.74	<.001
TRT(UB)	-14.888	10.698	45.53	-1.39	0.171
TR(B)	11.487	4.254	130.40	2.70	0.008
TRT(UB)*TR(B)	-19.048	4.370	64.59	-4.36	<.001
RFF(B)	1.974	3.280	32.32	0.60	0.552
TRT(UB)*RFF(B)	4.209	3.296	32.32	1.28	0.211
TR(B)*RFF(B)	37.260	4.281	131.80	8.70	<.001
TRT(UB)*TR(B)*RFF(B)	-0.570	4.187	131.80	-0.14	0.892
Log_{10} (Trial)	-19.275	9.389	43.87	-2.05	0.046

Note. Task-Relevance Type = TRT. *Use Blur* = UB. Target Resolution = TR. Blurred = B. Resolution First Fixated = RFF. Model was performed using effect coding [(Task-Relevance Type: *Use Blur* = +1, *Use Clarity* = -1) (Target Resolution: Blurred = +1, Clear = -1) (Resolution First Fixated: Blurred = +1, Clear = -1)]. dfDen = degrees of freedom used in the denominator.

There was a main effect of Log_{10} (Trial), such that participants became significantly faster to first fixate a singleton target across trials $F(1, 43.9) = 4.21$, $p = 0.046$. There was no main effect for *Task-Relevance Type*, $F(1, 45.5) = 1.94$, $p = 0.171$, which suggest that the blurred and clear target singletons did not significantly differ based solely on the *Task-Relevance Type*. However, there was a significant main effect for *Target Resolution*, $F(1, 130.4) = 7.29$, $p = .008$, and an interaction for *Task-Relevance Type x Target Resolution*, $F(1, 64.6) = 19.00$, $p < .001$, as well as *Target Resolution x Resolution First Fixated*, $F(1, 131.8) = 75.76$, $p < .001$. Thus, both interactions were further analyzed with a Tukey HSD tests (see Table 39 & 40, respectively). The main effect for *Resolution First Fixated*, the two-way interaction of *Task-Relevance Type x Resolution First Fixated* were all not significant. Importantly, the three-way interaction *Task-Relevance Type x Target Resolution x Resolution First Fixated* also was not significant. A Tukey HSD was still performed to compare when the blurred target singleton was fixated first for participants using clarity to guide search to when the clear target singleton was fixated first for participants using blur to guide search. The results showed that the two conditions did not significantly differ from one another. Therefore, the mean Log_{10} (RT) for a clear target singleton that was fixated first, which was responded to faster than when a blurred target singleton was fixated first, was no due to a difference in attentional deployment.

Table 39

Tukey HSD Comparisons – Task-Relevance Type x Target Resolution with Current Fixation Start

TRT	TR	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Use Clarity	Blurred	A	407.001	17.172	372.84	441.16
Use Blur	Clear	AB	354.251	16.678	320.99	387.51
Use Clarity	Clear	B	345.93	16.033	313.73	378.13
Use Blur	Blurred	B	339.129	15.525	307.93	370.33

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, Q = 2.637). Task-Relevance Type = TRT. Target Resolution = TR.

Table 40

Tukey HSD Comparisons – Target Resolution x Resolution First Fixated with Current Fixation Start

TR	RFF	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Blurred	Blurred	A	412.299	13.528	385.53	439.06
Clear	Clear	A	385.377	13.088	359.61	411.15
Blurred	Clear	B	333.831	12.17	309.64	358.03
Clear	Blurred	B	314.805	12.282	290.39	339.22

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, Q = 2.637). Target Resolution = TR. Resolution First Fixated = RFF.

As shown in Table 39 and Figure 29, the *Task-Relevance Type x Target Resolution* interaction (which collapses across levels of *Resolution First Fixated* factor), participants using clarity to guide search during a blurred target singleton trial produced the longest time to first fixate the singleton target. This result was significantly longer than using clarity during a clear target singleton trial or using blur during a blurred target singleton trial. However, when using blur to guide search during a clear target singleton trial, the amount of to first fixate the singleton target did not significantly differ from any of the other *Task-Relevance Type* x *Target Resolution* conditions. In general, these findings support that using blur or clarity when a unique item in that resolution is present results in faster first fixations to a letter. However, even when using blur to guide search it seems first fixating a letter when a clear target singleton is present is less difficult, then using clarity to guide search and first fixate a letter when a blurred target singleton is present.

As shown in Table 40 and Figure 29, the *Target Resolution x Resolution First Fixated* (which collapses across levels of *Task-Relevance Type*), participants were faster to first fixate a resolution opposite the resolution singleton. Participants were faster to first fixate a clear letter during the blurred target singleton trial and a blurred letter during the clear target singleton trial. The target singletons for both blur and clear target singletons took longer when they were fixated first than a clear or blurred distractor being fixated first. This is a difficult finding to explain because the previous analyses have suggested that unique clarity captures attention and unique blur weakly repels attention toward nearby clarity. These results suggest that clarity's capture and blur's repulsion are not due to the time required to first fixate a clear or blurred letter. If unique clarity captures, one might expect to see a faster selection process where the clear target singleton is selected and fixated first faster than other letters, but this is not supported by the data.

The main result and reason for this analysis was to investigate when the blurred target singleton was fixated first for participants using clarity to guide search to when the clear target singleton was fixated first for participants using blur to guide search. The results showed that the two conditions did not significantly differ from one another. Therefore, the mean Log_{10} (RT) for a clear target singleton that was fixated first, which was responded to faster than when a blurred target singleton was fixated first, was no due to a difference in attentional deployment.