THE EFFECT OF BLUR ON VISUAL SELECTIVE ATTENTION

by

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Abstract

The effect of blur/clarity contrast on selective attention was investigated in terms of how unique blur and/or clarity guides attention. Visual blur has previously been suggested to be processed preattentively using a dual-task paradigm (Loschky et al., 2014). Experiments 1 and 2 used rotated L and T visual search tasks with blur/clarity contrast being manipulated such that it was non-predictive of the target's location. Each experiment was preceded by a legibility control study such that blurred and clear letters had similar accuracy and reaction times. This allowed for the results to be interpreted as changes in attention rather than difficulty identifying the letters because they were blurry. Results suggest that when non-predictive of target location, unique blur plays a passive role in selective attention in which it is ignored, neither capturing nor repelling attention to its spatial location, whereas unique clarity captures attention. The findings provide insight to the role that blur/clarity contrast plays in guiding visual attention, which can be implemented in visual software to help guide selective attention to critical regions of interest displayed on a computer screen.

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Chapter 1 - The Effect of Blur on Visual Selective Attention

In film, one technique that directors use to guide their audience's attention is to use depth of field to focus in on objects or people of interest making them appear clearly and thereby blurring other areas of less relevance in the scene at other distances. In Figure 1 below there is a simplified version of this technique to provide an example of how blur/clarity contrast guides attention. When viewing the short clip (2 seconds), answer these two questions: 1) At the beginning of the clip do you first look at the L or the T? 2) At the end of the clip, which are you looking at?

Figure 1. KSU Blur/Clarity Guidance Example. Peterson (2016) https://youtu.be/_m8Bs8HeIQ4.

This brief clip should demonstrate that the visual clarity of the scene can guide your selective attention to look first to the T and end on the L. Several interesting questions emerge from this simple demonstration related to blur and how it either captures, repels, or is ignored by selective attention when it is a unique item. According to Treisman and Gelade (1980), features such as orientation, spatial frequencies, and color, among others, have been argued to be preattentive features that can be processed in parallel without attention. A recent finding from Loschky et al. (2014), in which blur detection was unaffected by cognitive load, suggests that blur is preattentively processed. Visual blur is also largely avoided by eye movements (Khan, Dinet, & Konik, 2011; Loschky & McConkie, 2002). This seems to then make blur unique among preattentively processed stimulus features. Specifically, features that are preattentively processed have generally been shown to capture attention (Joseph, Chun, & Nakayama, 1997), leading to *pop out* when unique (Treisman & Gelade, 1980). Yet, blur when task irrelevant is often ignored even when unique (Enns & MacDonald, 2012).

Preattentive versus Attentive Processing in Visual Search

According to Treisman and Gelade's (1980) feature integration theory (FIT), a preattentive feature can be processed in parallel, namely simultaneously across the visual field, with other preattentive features. According to FIT, preattentive features have specialized populations of cells in the brain that can process the visual stimuli without attention being needed. Visual search has previously been used to provide evidence of such preattentive features (Treisman & Gelade, 1980). This can be shown in a feature search task, which is when a specific feature such as color or a line orientation differs significantly from all other features displayed, for example a red square target amongst green square distractors. In such feature search tasks, as set size increases, the red square will continue to pop out as observed by reaction times (RT). As set size increases, the RT x set size slope should remain approximately constant (e.g., < 10 msec/item) (Treisman & Gelade, 1980). However, when viewing objects in the real-world environment, they are usually not made up of only one single feature, but are complex objects made up from multiple features, thus attention is required to find the object of interest when it is not alone. For example, finding your car in a parking lot full of other cars will require an attentive search when the other cars share features of your car such as the color or shape and no single feature is unique to your car. Instead, a combination of correct features is required to make up your car and attention is required to bind those features together to identify your car amongst the other cars.

The attention stage is required when more than one feature needs to be bound to create an object in order to identify it. When the RT x set size slope does increase (e.g., 20-30 msec/item), then it is taken to suggest that attention is required to find the target (Wolfe, 2007). Treisman and Gelade (1980) would argue that this is because attention is required to bind separate features together to find the target. This is found in conjunction searches, where at least two features are necessary to uniquely identify a target, because those same features are shared amongst the distractors, but not in the same combination. For example, the target may be a red O amongst red Xs and green Os as distractors (Wolfe, Cave, & Franzel, 1989). With such conjunction searches, it has typically been found that as set size increases, the RT also increases suggesting serial processes requiring attention (e.g., Treisman & Gelade, 1980; Wolfe et al., 1989).

The difference seen between feature and conjunction searches is how the search is performed. If it is a feature search, it can be accomplished with parallel processing across the field of view. Whereas in a conjunction search, attention is required and a serial process occurs to find the target or determine its absence. An alternative explanation to how a difficult conjunction visual search is performed is through a resource limited parallel process, in which less relevant items are not fully processed as the perceptual load of a given task increases (Lavie, 1995). Moving forward, we will focus on the two stage attentional model. While this implies that two separate processes are occurring and is in line with Treisman and Gelade (1980), Wolfe (1989) has suggested that the *parallel* and *serial* processes are not as separate as argued by Treisman and Gelade. Wolfe (2007) argues that the parallel processes can feed into serial processing, thus they may not be two separate systems. A serial process is when one or a small number of items are processed at one time and when the target is not present there, attention must be moved to a new location to process other items. When attention is required to move, it takes time (Posner, 1980). Thus, when set size increases and attention is required, the number of items that need to be attended increases, so the RT will increase. In general, when serial processing is occurring, the RT x set size slopes for target-absent versus -present trials have a 2:1 ratio (Wolfe, 1989).

Another serial search task is a spatial configuration search, where features are searched amongst the target and distractors, but the features' spatial relationships to one another differ between the target and distractors. A well-established spatial configuration search is a rotated L versus T search task (Wolfe et al., 1989; Egeth & Dagenbach, 1991; Jiang & Chun, 2001). Egeth and Dagenbach (1991) provided evidence that an L and T search task may be processed in parallel if the letters are not rotated, whereas if the letters are rotated, then the task is processed serially. Chun and Jiang (1998) used an L and T task which was still serially processed when the T target was only rotated 90° to the left or right from the upright position, and the L distractors had four rotations (0° upright, 90°, 180°, and 270°). Adding further difficulty to the rotated L and T task, Jiang and Chun (2001) made the distractor Ls look more T-like by offsetting the lines to bring one line closer to the center of the other line, making the L appear more T-like. Similar stimuli to Jiang and Chun (2001) will be used in Experiment 2 as well as its pilot.

Attentional Capture

Preattentive features have been argued to *involuntarily* guide attention suggesting that a feature is *capturing* selective attention to its location (Wolfe, 2007). In a feature search, the target having one unique feature (a *singleton*) makes it highly salient (Itti & Koch, 2001). Itti and Koch (2001) argue that the degree to which something is salient in a search task, depends on the feature differences between the target and its distractors. A red square among green squares is highly saliently because it has a unique color feature which is easily distinguishable from its distractors, and having a homogenous set of distractors will also increase the target's pop out (Wolfe & Horowitz, 2004). Therefore, it is not only the features of the target that makes it salient, but the features of the surrounding distractors also influence the saliency of the target. If the target was amongst a more heterogeneous set of distractors, such as a red square amongst green, blue, orange, yellow, and purple squares, then the saliency of the target would be reduced (Wolfe & Horowitz, 2004). The saliency of the target decreases in heterogeneous distractor sets because there are more initial low-level features being included in a feature map, which will eventually result in a saliency map where the most salient item will capture selective attention in a winner-take-all fashion (Itti & Koch, 2001). In the case of the red square among green squares the distractors are all green, which together allows for the red target singleton to be highly salient and be the winner by capturing selective attention.

When a target has a unique preattentive feature it can be considered a singleton. Singletons typically involuntarily pop out by capturing attention, such as in a feature search (Treisman & Gelade, 1980). Theeuwes et al. (1998) using the Oculomotor Capture paradigm had participants perform a visual search task and were instructed to identify the color singleton target. When the color singleton target was simultaneously presented with a new object that suddenly onset, then selective attention was captured and an eye movement went to the location of the abrupt onset distractor on approximately half of the trials. Theeuwes et al. (1998) showed that attention could be captured by an abrupt onset of a new object even when it was, according to their definition, task-irrelevant, therefore the abrupt onset was never located at the target nor helpful in making a correct answer. Furthermore, not only was covert attention captured (i.e., attention at a separate location from the point of fixation), but eye movements (overt attention) were also frequently made to the sudden onset distractor. However, it makes sense that overt attention would follow covert attention because a precursor to making an eye movement to a location is that covert attention first be moved to that location (Corbetta, 1998; Corbetta et al., 1998; Deubel & Schneider, 1996; Hoffman & Subramanian, 1995). Theeuwes et al. (1998) found overt attention captured to onset distractors on ~50% of trials, which is similar to a number of other studies that have found capture rates that have ranged from 5-40% (Belopolsky, Kramer, & Theeuwes, 2008; Boot et al., 2005; Irwin, Colcombe, Kramer, & Hahn, 2000; Kramer, Hahn, Irwin, & Theeuwes, 2000).

Theeuwes (1991) showed that attentional capture can occur to an abrupt onset or offset's spatial location when non-predictive of the target's location, namely the abrupt onset and offsets occurred at all locations equally often (regardless of whether a distractor or target was there). Yantis and Jonides (1984) have also shown an abrupt onset will capture attention. However, Yantis (2000) argued that attention is not always captured by singletons when they are not task-relevant. Instead, top-down processes can override bottom-up attentional capture such as from an abrupt onset, if there is enough time for the top-down process to implement a goal-orientation for detecting a target. This was also supported by Theeuwes et al. (1998) in Experiment 2 where they cued covert attention to go to the location of the target prior to the abrupt onset occurring. Once covert attention was already placed at the target's location, the abrupt onset no longer captured attention in the same manner as when the abrupt onset of a new object and color target singleton appeared simultaneously in Experiment 1 (Theeuwes et al., 1998). However, Yantis and Egeth (1999) have shown that singletons that are non-predictive of a target's location do not necessarily capture attention, even when salient. They found evidence of capture of selective attention to non-predictive target locations only for singletons that varied by features on a *prothetic* dimension, namely a dimension with quantifiable directionality such as size (i.e., varying degrees of size) or luminance (i.e., varying degrees of brightness). However, they did not find capture to non-predictive target locations for singletons that varied by features on a metathetic dimension, namely qualitative feature differences such as color (e.g., red target versus blue distractors). In the current experiments, the term *task-irrelevant* will be used in line with Yantis and Egeth (1999), to refer to singletons that are *non-predictive* of the target's location, because the singletons are distributed equally across all locations in the display (whether target or distractor).[1]

Effects of Blur On Attention

As with Theeuwes' (1991) findings that both abrupt onsets and offsets will capture selective attention, so too can unique blur and clarity be thought as being the opposite sides of the same coin capturing selective attention when unique. Typical visual search findings support that unique items pop out (Triesman & Gelade, 1980). In a typical feature search such as for a red square target amongst green square distractors, the red square will pop out, but it is also expected that a green square target amongst red square distractors would also pop out. Therefore, it is simply a matter of uniqueness in the search display capturing attention to the most salient item (Itti & Koch, 2001). As noted above, Loschky et al. (2014) have provided evidence that visual blur is another preattentive feature by showing that blur detection was unaffected by cognitive load. One may expect then that both unique blur and clarity would produce similar outcomes to other preattentive features, namely that when unique, both blur and clarity should capture attention, just as unique color (red among green, or green among red) or an abrupt onset or offset would capture selective attention.

However, blur may not capture attention in a similar fashion as found with other preattentive features. The counterpart to blur is visual clarity, which does appear to capture attention like other preattentive features when unique, as shown in a number of eye movement studies (Enns & MacDonald, 2012; Khan, Dinet, & Konik, 2011; Loschky & McConkie, 2002; Smith & Tadmore, 2012). Enns and MacDonald (2012) tracked participants' eyes while they viewed images in preparation for a new/old recognition test, and unknown to the participants, the images were manipulated to have a region on the left or right side that was sharpened or blurred compared to the rest of the image. The authors found that regions of sharper clarity were looked at earlier, longer, and more often than regions that were blurred. Similarly, Khan, Dinet, and

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[1] Yantis and Egeth (1999) refer to singletons that are non-predictive of a target's location as *task-irrelevant*, whereas Theeuwes et al. (1998) refer to singletons that *never* occur at the target location as *task-irrelevant*. Yantis and Egeth refer to this type of task-irrelevant singleton as *unpredictive* (or one might say, anti-predictive) of the target location, because ideally it should be actively ignored.

Konik (2011) tracked participants' eyes while they freely viewed images that were manipulated to either have the entire image presented clearly or the entire image blurred except for one selected sharp region. When the entire image was clear, gaze was distributed throughout the image, whereas gaze was found to be directed at the sharper region in an image that was otherwise blurred. However, unlike in the Enns and MacDonald (2012) study, in the Khan et al. (2011) study, an issue is that there was no uniquely blurred region on a clear background to compare with the results of the uniquely clear region. Smith and Tadmore (2012) found results similar to the previous two studies discussed (Enns & MacDonald, 2012; Khan, Dinet, & Konik, 2011). Participants fixated the center of the screen, and then were presented with a 3 x 3 grid of images missing the central image (i.e., 8 total images), and were simply instructed to freely view the images, which were shown for five seconds. Importantly, all 8 images were different versions of the same base image that had varying levels of blur, from no blur to considerable blur. They found that images with no or very little blur were fixated first, and that viewers spent the most time looking at the clearer images. While presenting images with varying levels of blur is helpful in identifying how gaze behavior changes with different levels of blur, there is an issue that the no-blur images may have captured attention because they were singletons. More specifically, the no-blur images may have captured attention because they were unique by being the only images with higher spatial frequencies. As with the Khan et al. (2011) study, it would have been beneficial to have a single image that was blurred and the other images presented clearly. It is unclear how blur may be responded to in that type of a situation. It might capture attention by being a singleton amongst clear images.

Conversely, blur might instead repel attention from its spatial location if blur is being avoided. Loschky and McConkie (2002) provided evidence that blur may be avoided. They used a gaze-contingent multiresolutional display in which a circular region centered on the viewer's point of gaze was shown clearly (a *moving window*), and outside of the window, the image was shown blurred. They then varied the size of the window of clarity, and varied the degree of blur outside the window. They found that during visual search, with relatively high levels of blur, as window size decreased, saccades became shorter compared to the unblurred condition. The results suggested that having high levels of blur in the visual periphery reduces the likelihood of competing objects to be selected for attention compared to objects inside the clear window. These findings suggest blur may lose in a winner-takes-all type competition against clear objects. If so, then if Smith and Tadmore (2012) and Khan et al. (2011) had included a blurred image singleton as previously suggested, one might not find attention captured by the singleton, but instead, the one blurred image might be the last image fixated, which would suggest that blur repels attention.

There is evidence to suggest a third alternative effect, or in this case a lack of an effect, of blur on selective attention. The results from Enns and MacDonald (2012) were previously discussed to support the idea that in the presence of blur, unique clarity captures attention. However, is the reason that unique clarity is capturing attention simply the result of blur repelling attention from blurred spatial locations (Loschky & McConkie, 2002)? There is evidence from Enns and MacDonald (2012) inconsistent with the latter idea. In their Experiment 3, they showed that participants were equally likely to look at a region of an image whether it was uniquely blurred or when the entire image was uniformly blurred. This does not suggest that active avoidance of blur is occurring, but instead that blur is simply being ignored rather than capturing or repelling selective attention. If blur were being actively avoided by repelling selective attention from its spatial location, then the uniquely blurred region would have had fewer eye movements to its region compared to when the entire image was uniformly blurred. Therefore, based on the existing literature, it seems possible that unique blur may capture attention (like color singletons or onsets and offsets), repel attention, or simply be ignored by selective attention.

Research Questions

Experiment 1 investigated if visual blur would capture, repel, or be ignored by selective attention? Experiment 2 investigated the same question as Experiment 1, but attempted to amplify the effects found in Experiment 1 through set size manipulations (4 vs. 8), and by increasing distractor difficulty by making the L distractors appear more T-like, and by presenting the search items further in the visual periphery.

Hypotheses

The effects of blur and clarity on selective attention could potentially work in at least three different ways, each of which is stated in terms of an alternative competing hypothesis below and illustrated in Figure 2.

1) *Blur captures:* Attention is drawn to contrast between clarity and blur, and this contrast is maximized for either blur or 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 or not, and unique clarity captures attention only in contrast to blur.

These three alternative hypotheses regarding the blur/clarity relationship to selective attention can be tested by comparing visual search RTs in conditions with either blurred or clear singletons and all-blurred and all-clear arrays.

Generalized Graphical Representations of Predicted Model Hypotheses

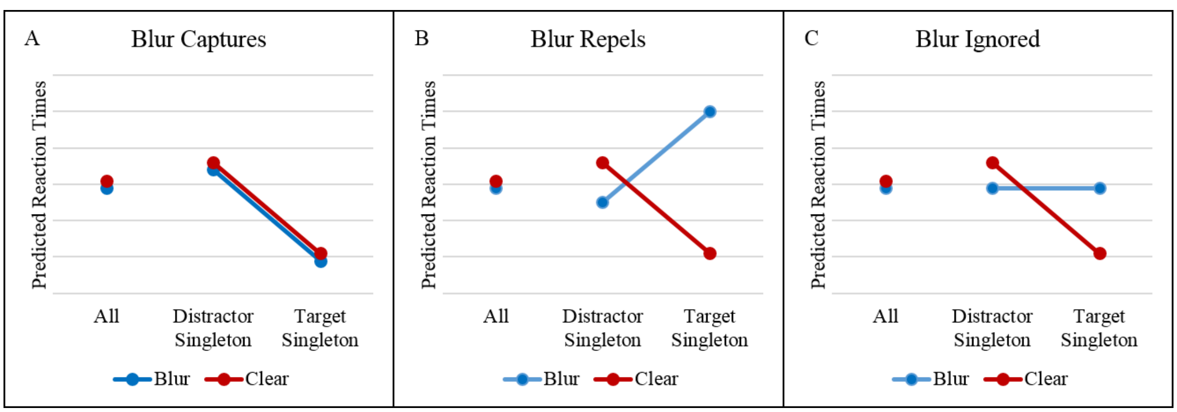

Figure 2. Generalized hypothesized reaction times based on predicted average number of items searched. Across all hypotheses (A-C), when there is no blur/clarity contrast (the all-blur and all-clear conditions), random search is predicted to occur for the target, producing a baseline search time. All three hypotheses make essentially the same predictions for the clear conditions, such that clear singleton items capture attention producing faster target singleton detection RTs, and clear singleton distractor RTs are predicted to be slightly slower because attention will first be moved to the distractor, increasing the average number of items searched compared to random search. The three hypotheses differ in terms of the predicted RTs for the blurred singleton target and blurred singleton distractor conditions: A) *Blur Captures* predicts identical results for the

clear and blur singleton conditions which will capture attention, otherwise random search will follow until the target is found. B) *Blur Repels* predicts that blur singleton items will be the last item searched, thus producing longer RTs for the blurred target singletons, but shorter RTs when a blurred distractor singleton is present due to a reduction in set size relative to random search. C) *Blur Ignored* predicts that when there is a blur singleton, it neither repels nor captures attention resulting in purely random search. Note: In the predictions for the Blur Captures hypothesis, and the predictions for the all-blur versus all-clear conditions, the predictions for the blur conditions have been ever-so-slightly lowered on the graph so as not to overlap with the clear conditions. However, this is only for the ease of visually presenting those predictions.

Quantitative Models Predicting the Hypothesized Average Items Searched

For both Experiments 1 and 2, the predicted models for the three hypotheses shown in Figure 2 were calculated based on the number of items that would, on average, be required to be attended before finding the target for a given condition. The calculations were made based on six assumptions.

Assumptions of the Quantitative Models

Below are the assumptions used in modeling the three alternative competing hypotheses. Note that these assumptions are almost certainly overly simplified. However, the value of these simplified assumptions is that they allow for the general relationships between conditions in each of the three hypotheses to take form quantitatively.

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.[2]

Each of the hypothesized search RT averages were calculated by summing the probability of each item in an array needing to be searched given that the target was or was not found on the previous item (see Table 1). This average made the simplifying assumption that at least one item must be attended in order to find the target, so the smallest search average would be one, whereas the largest search average would equal the set size (See Appendix A for detailed calculations).

Table 1

Predictions for Experiment 1 & 2 for each Condition's Average Number of Items Searched

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

Note. SS = Set Size. Clarity refers to whether the target was presented clearly or blurred. Condition refers to the relative distance from the unique item to the target (e.g., Blurred Far means the item farthest from the target is the only item blurred), and includes the All-conditions where no unique items are present.

[2] Again, this assumption is certainly overly simplified, and adopted only to more easily quantify the hypothesized relationships between conditions.

Chapter 2 - Pilot Experiment 1

Method

Experiment 1 was preceded by a legibility control study done to verify that blurred and clear letters had similar accuracy and reaction times. Such a result in Pilot Experiment 1 would allow for the results in Experiment 1 to be interpreted as changes in selective attention rather than difficulty identifying the letters because they were blurry.

Participants

There were 37 participants from Kansas State University's (KSU) undergraduate research pool (25 females, mean age = 19.6). Participants' vision was tested and was 20/30 or better. All participants were naïve at the beginning of the pilot. All participants gave their informed consent and participated for class credit.

Apparatus and Stimuli

Stimuli were presented on 17-inch Samsung SyncMaster 957 MBS monitors set to a refresh rate of 85 Hz, and 1024 x 768 pixels. Using chin rests, participants' eyes were 53.34 cm from the monitors for 37.8° x 28.7° of visual angle. The monitors were calibrated using 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. Participants made responses on Cedrus model RB-834 response pads. Figure 3 displays the 16 images: 4 clear L images with four rotations (0 upright, 90, 180, 270), 4 blurred L images with same rotations, and 4 clear T and 4 blurred T images with the same rotations. All images were created in Microsoft Paint. The clear L images were 24 pixels (0.89° of visual angle) for the horizontal line and 44 pixels (1.65° of visual angle) for the vertical line length of an upright L. Both lines have a width of 4 pixels (0.15° of visual angle). The clear T images were 33 pixels (1.23° of visual angle) for the horizontal line and 44 pixels (1.65° of visual angle) for the vertical line length of an upright T. Both lines have a width of 4 pixels (0.15° of visual angle). The blurred images were created by using low-pass filtering in MATLAB which produced L and T images with a spatial frequency cut-off value of 0.25 cpd. The blurred images were then standardized to have the same mean and standard deviation luminance values as the clear letters using Mathworks MATLAB 2014b, with image processing toolbox (ver. 9.1). The letters, fixation cross, and background all had a mean luminance value of 127. The images were placed at five potential locations along a centered invisible circle set to a radius of 3° degrees of visual angle. The letters appeared at the following locations on the circle: 0° (top), 72°, 144°, 216°, and 288°.

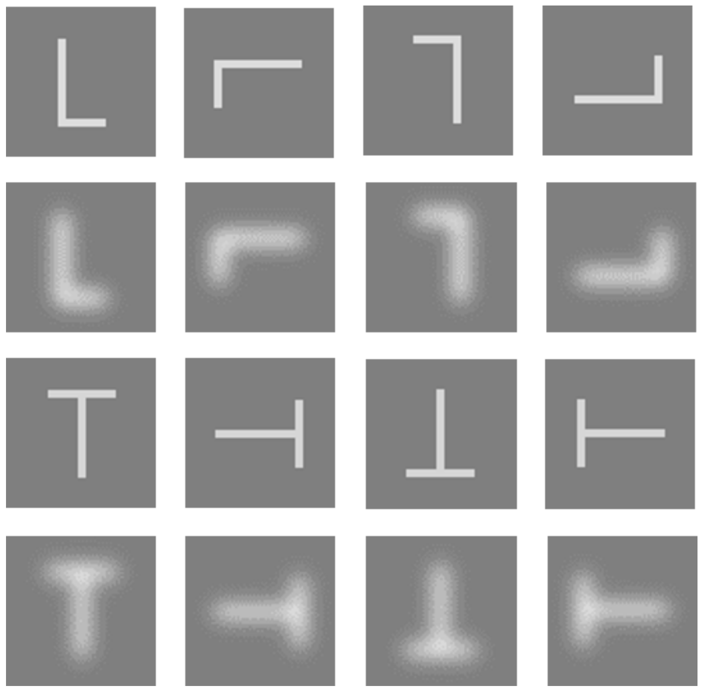

Figure 3. Images of the L and T blur/clear letter rotations. Row 1 clear L rotated (0, 90, 180, and 270). Row 2 blurred L with same rotations. Row 3 clear T with same rotations as the L letters. Row 4 displays the blurred T letters with the same rotations as the other letters displayed.

Design

The experiment was a 2 (Letter: L vs. T) x 2 (Clarity: Clear vs. Blurred) within-subjects design. The following manipulations were all counterbalanced during the experiment: presence of single T or single L, blur or clear, and the five locations where the letter was presented. However, due to a systematic error in the data set creation, the location was incorrectly counterbalanced, though consistently across all participants (see Appendix B). There were 20 blocks which each had 20 trials. All 400 trials were randomized across each participant's experimental session. The rotation of each letter was randomized on each trial. The dependent variables were accuracy for the identification task and RT.

Procedure

Participants first read and gave their informed consent, then their visual acuity was tested using the Freiburg Visual Acuity and Contrast Test (FrACT) (Bach, 1996; Bach, 2007). Participants then read instructions to the experiment. Figure 4 shows a trial schematic.

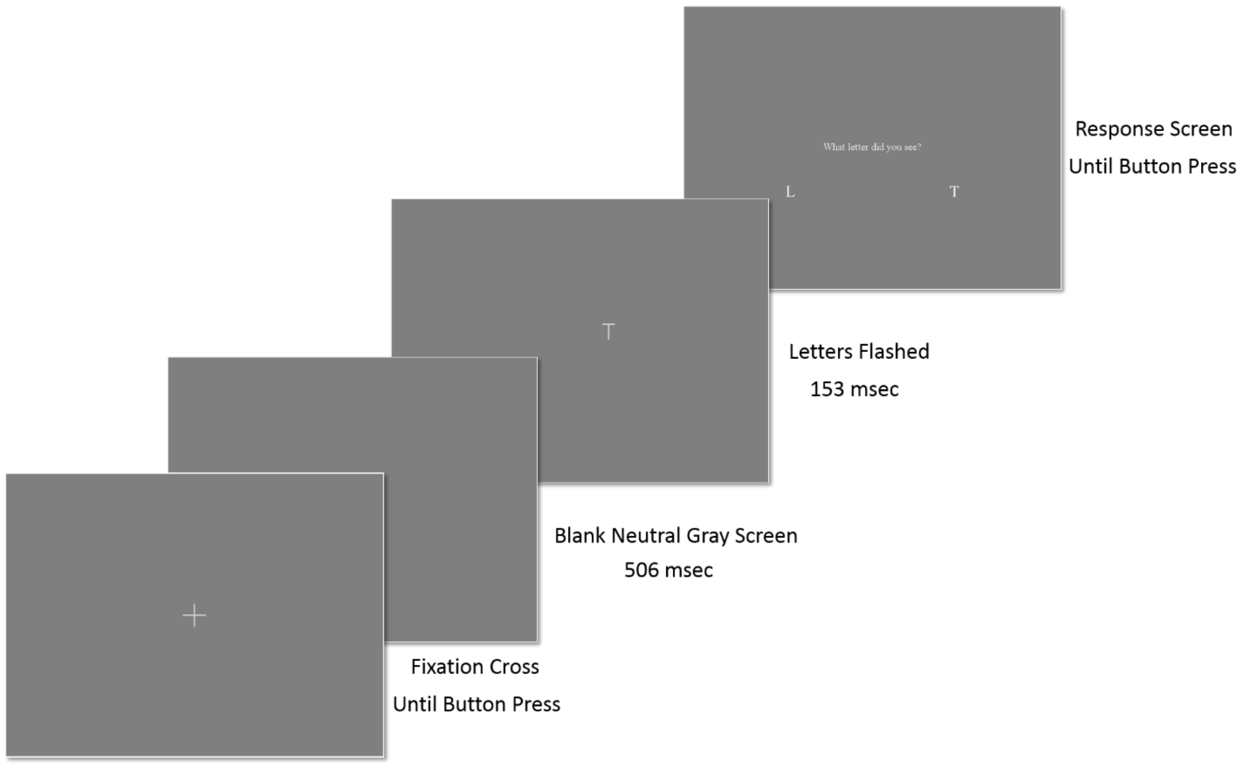

Figure 4. Trial schematic.

As shown in the Figure 4 trial schematic, the trials began with a fixation cross at the center of the screen, and participants hit the next button on the response pad to initiate the trial. A blank neutral gray screen was presented for 506 msec, followed by a single L or T letter for 153 msec to prevent eye movements to the letter while present. The response screen then appeared on the screen, asking, “What letter did you see?” (L and T options below), and remained until the response. The participant pushed the left response button to indicate an L or the right response button to indicate a T. Participants were allowed to quit or take a break at any time during the experiment, and every 100 trials the participants took a required break. There were a total of 400 trials. After finishing the experiment, participants read through a debriefing form and were thanked for their participation.

Pilot Experiment 1 Results

Prior to cleaning any of the data the overall accuracy across all trials was 96%. The data was then cleaned by first removing all reaction times < 150 msec or > 10 seconds. This resulted in one trial being removed from 14800 trials (0.007% of all trials).

The analyses of accuracy were conducted with the R statistical software (version x64 3.1.1) to run a multilevel logistic regression for binary data. Prior to analyzing the models, the categorical *Letter* and *Clarity* variables were effect coded as Letter (L = +1, T = -1) and Clarity (Blurred +1, Clear -1). From the analyses, the best model was Accuracy ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (1|Participant) (BIC = 4495.8) compared to the second best model which included the random effect of (Letter|Participant) (BIC = 4510.4) (See Appendix C for all models with BIC values). Table 2 displays the parameter estimates for the fixed effects and random effects variance from the best model.

Table 2

Parameter Estimates for Accuracy ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (1|Participant) Model

Fixed Effects	Estimates	Std Error	z-value	p(z)	Random Effects Variance
Intercept	4.018	0.291	13.83	< 0.001	0.881
Letter(L)	0.207	0.044	4.71	< 0.001	
Clarity(Blurred)	-0.034	0.044	-0.78	0.438	
Log_{10}(Trial)	-0.177	0.108	-1.64	0.102	
Letter(L) x Clarity(Blurred)	0.015	0.044	0.33	0.739	

Note. Model was performed using effect coding [(Letter: L = +1, T = -1)(Clarity: Blurred = +1, Clear = -1)].

Figure 5 displays the mean transformed accuracy values back to proportion from logit space for the clear and blurred Ls and Ts at the end of the experiment. There was a significant main effect for Letter, suggesting that Ls were slightly, but statistically significantly easier to identify than Ts. No other fixed effects were significant, indicating that Ls were slightly easier to identify than Ts. However, much more importantly, it did not matter if they were presented clearly or blurred and this did not significantly change throughout the experiment.

Figure 5. The mean accuracy for each letter presented clearly or blurred. Error bars = 95% CI after being transformed back from logit, therefore the error bars are asymmetrical, having slightly longer negative error bars.

Prior to analyzing the data for reaction times, there was further cleaning of the data such that all of the incorrect responses were removed. From the 14,799 total trials, 563 trials were removed due to being incorrect responses (4% of trials) for a total of 14,236 trials.

The analyses were conducted using a linear multilevel model with effect coding in JMP Pro 12. The model analyzed was Log_{10}(RT) ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (Letter + Clarity + Letter x Clarity + Log_{10}(Trial)|Participant) with R^2 = .33, adjusted R^2 = .33, RMSE = 0.11. Table 3 displays the parameter estimates for the model.

Table 3

Parameter Estimates from Log_{10}(RT) ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (Letter + Clarity + Letter x Clarity + Log_{10}(Trial)|Participant)

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	2.868	0.020	60.93	140.60	<.001
Letter(L)	-0.009	0.002	35.98	-4.42	<.001
Clarity(Blurred)	0.001	0.001	35.76	0.68	0.504
Letter(L) x Clarity(Blurred)	-0.002	0.001	35.78	-2.01	0.052
Log_{10}(Trial)	-0.073	0.008	35.97	-9.20	<.001

Note. Model was performed using effect coding [(Letter: L = +1, T = -1) (Clarity: Blurred = +1, Clear = -1)]. DFDen = degrees of freedom used in the denominator.

Table 4 presents the Log_{10}(RT) marginal means (*M*) with within-subject standard deviations (*SD*), and the untransformed RT (RT*) geometric means (*GM*) with geometric within-subject standard deviations (*GSD*) for the clear and blurred Ls and Ts in milliseconds (msec). Figure 6 displays the Log_{10}(RT) *M* and standard error of the means (*SEM*) for *Clarity* x *Letter* in msec with RT* *GM* on secondary y-axis. The linear multilevel model, Log_{10}(RT) ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (Letter + Clarity + Letter x Clarity + Log_{10}(Trial)|Participant) was analyzed for significant main effects and an interaction. There was a significant main effect for Log_{10}(Trial), $F(1, 36.0) = 84.64$, $p < .001$, indicating that participants responded faster as they progressed through the experiment. There was a significant main effect for Letter, $F(1, 36.0) = 19.52$, $p < .001$, with Ls significantly faster to identify than Ts. Most importantly, there was no significant main effect for Clarity, $F(1, 35.8) = 0.46$, $p = .504$, indicating that blurred and clear letters were identified at similar rates. There was also no significant interaction effect between Letter x Clarity, $F(1, 35.8) = 4.05$, $p = .052$, indicating that one letter was not identified faster or slower than the other letters because of a specific clarity level. Nevertheless, two planned contrasts compared the levels of *Clarity* for each *Letter*. Neither the contrast between the blurred and clear Ls, $t(35.8) = -0.79$, $p = .432$, nor the contrast between the blurred and clear Ts, $t(35.8) = 1.81$, $p = .074$ were significantly different. Importantly, these results showed that within each letter, neither the accuracy nor the Log_{10}(RT)s were significantly different when presented as clear or blurred, thus legibility was controlled for. Therefore, any differences in RTs for Experiment 1 should be minimally affected by the blurred letters being more difficult to identify.

Table 4

Letter x Clarity: Log_{10}(RT) M with SD and RT GM with GSDs*

Letter	Clarity	Log_{10}(RT) M	Log_{10}(RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
L	Blurred	2.699	0.105	500	392	637
L	Clear	2.701	0.106	502	393	642
T	Blurred	2.721	0.121	526	398	694
T	Clear	2.717	0.122	521	394	690

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.

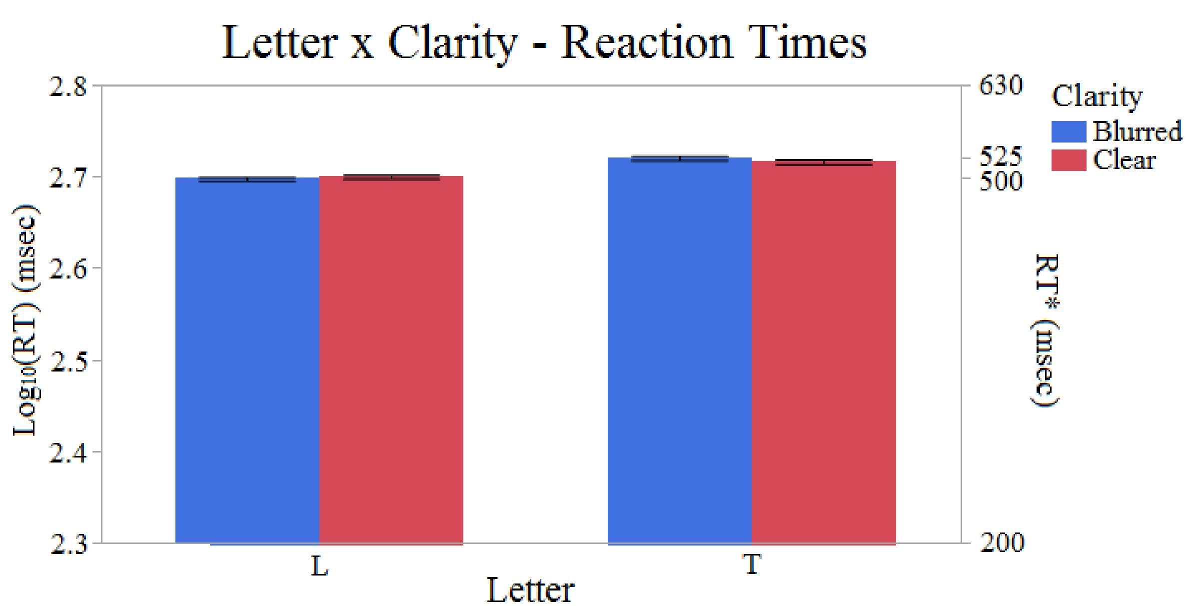

Figure 6. The Log_{10}(RT) marginal means for each letter presented clearly or blurred with +/- 1 SEM bars. RT* GMs are also presented on the secondary y-axis.

Chapter 3 - Experiment 1

Method

Experiment 1 investigated whether unique blur and clarity's influence on selective attention would be to capture, repel, or be ignored. This was accomplished through a rotated L versus T search task where *Clarity* was manipulated to be non-predictive of target location in order to measure its influence on selective attention as measured by effects on RT. Changes in RTs can be interpreted as changes in guiding selective attention rather than legibility based on the results of Pilot Experiment 1.

Participants

There were 57 participants from Kansas State University's (KSU) undergraduate research pool (47 females, mean age = 19.1). Participants' vision was tested and was 20/30 or better. All participants were naïve at the beginning of the experiment. No participant was in both the Experiment 1 pilot and Experiment 1. All participants gave their informed consent and participated for class credit.

Apparatus and Stimuli

All the apparatus and stimuli were the same as in Pilot Experiment 1. However, as shown in Figure 7, there were five letters simultaneously present along a centered invisible circle set to a radius of 3° degrees of visual angle. The letters appeared at five locations of the circle at 0° (top), 72°, 144°, 216°, and 288° on each trial. The center-to-center letter distances were used to calculate a Bouma's constant of 0.59, which indicated that crowding should not have influenced the search task (Bouma, 1970).

Design

The experiment used a 2 (Clarity: Blur vs. Clear) x 4 (Condition: All, Far, Mid, & Target) within-subject design. Figure 7 provides examples of the conditions. Counterbalancing of the 320 trials resulted in a number of different nested variables, including target present/absent (160 trials each), target clear/blurred (80 trials each) appearing equally often at each of the five locations. This resulted in 16 trials for each target present that was either clear or blurred and at one of the five locations. The same counterbalancing was done for the target absent trials in which an L distractor was clear/blurred at one of the five locations. The rotations of the letters were randomized on each trial. The dependent variable was correct RT for the target present/absent task.

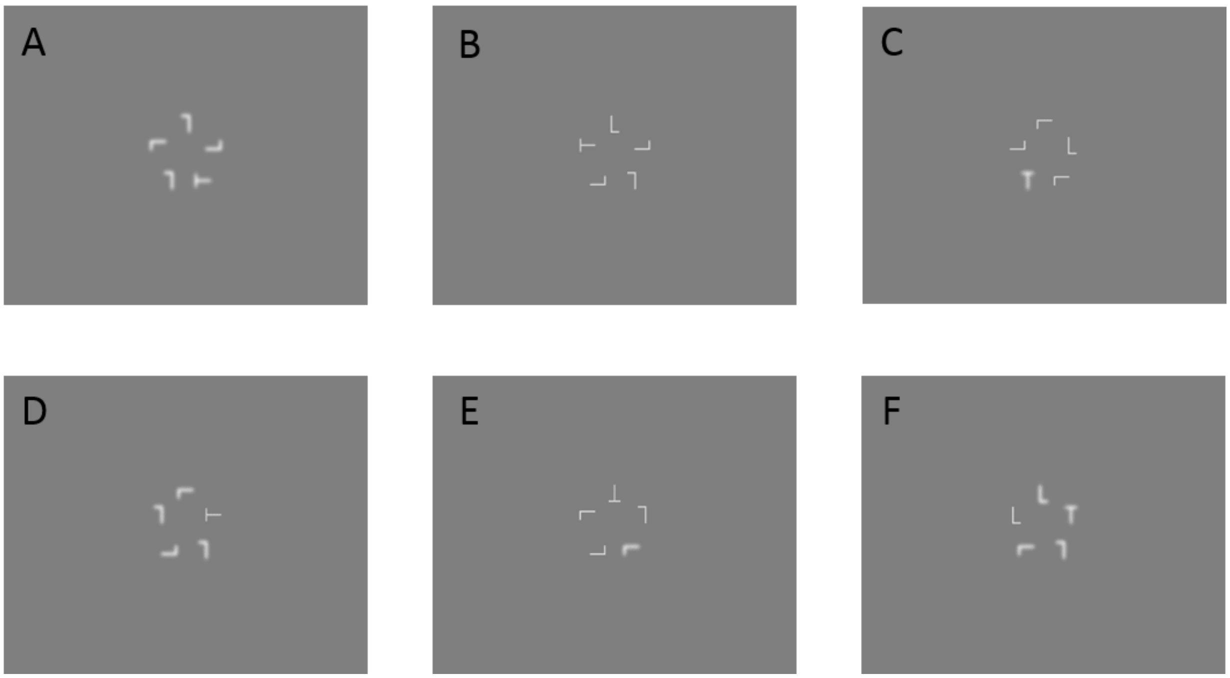

Figure 7. Examples of the clarity manipulation conditions are A). All-blurred, B). All-clear, C). Blurred Target Singleton, D). Clear Target Singleton, E). Blurred Far Distractor Singleton, and F). Clear Far Distractor Singleton. There were also unique clear mid distractor singletons, though they are not shown due to similarity to the far distractor singleton conditions.

Procedure

Participants first read and gave their informed consent, then their visual acuity was tested using the Freiburg Visual Acuity and Contrast Test (FrACT) (Bach, 1996; Bach, 2007). Participants then read instructions to the experiment. The experiment had 320 trials. Figure 8 shows a trial schematic.

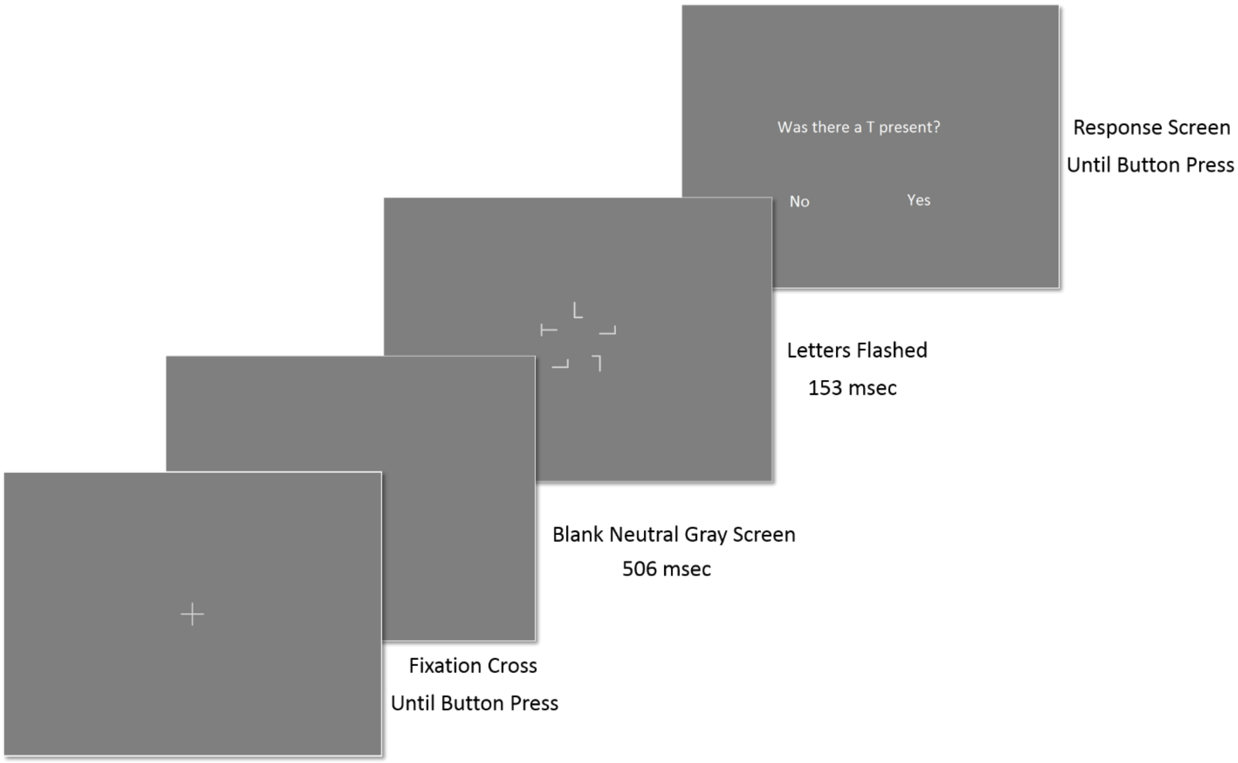

Figure 8. Trial schematic.

As shown in the Figure 8 trial schematic, the experiment started with a fixation cross at the center of the screen, and participants hit the "NEXT" button on the response pad to begin the trial. A blank neutral gray screen was presented for 506 msec, followed by five letters for 153 msec to prevent eye movements to the letters. The response screen then replaced the letters on the screen, asking, "Was there a T present?" (Yes and No options below), and remained until the response. The participant pushed the "YES" (right) or "NO" (left) button on the response pad. Participants were allowed to quit or take a break at any time during the experiment, and every 80 trials the participants took a required break. There were a total of 320 trials. After finishing the experiment, participants read through a debriefing form and were then thanked for their participation.

Experiment 1 Results

Due to computer errors in recording of data, data from three participants were lost. The data was then filtered to select for only *singleton* and *all* blur/clear manipulation trials that were relevant to the analyses, with the filtered trials being fillers that were necessary to include in the stimulus set in order to ensure that blur/clarity was non-informative about the identity of the target. This resulted in 14,820 trials being removed from 18,239, leaving 3,419 trials. Prior to cleaning the selected data, the overall accuracy across all trials was 83%. The data was then cleaned by first removing all RTs that were < 150 msec or > 10 seconds (2 trials), and all incorrect responses were removed (589 trials).

The following analyses are all completed using Log_{10}(RT) because of the non-normal distribution of the raw reaction time data. Three linear multilevel models with effect coding in JMP Pro 12 were performed to determine the best approach at explaining the variance within the data. Table 5 displays the parameter estimates for the best model analyzed, Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) with R^2 = .47, adjusted R^2 = .47, RMSE = 0.12, BIC = -3618.8.[3]

Table 5

Parameter Estimates from Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	3.188	0.031	56.55	103.90	<.001
Clarity[Blurred]	0.001	0.003	52.66	0.41	0.680
Condition [All]	-0.003	0.004	280.80	-0.66	0.507
Condition [Far]	0.007	0.004	114.93	2.07	0.041
Condition [Mid]	0.016	0.004	117.91	4.44	<.001
Condition [Blurred] x Condition [All]	0.008	0.005	272.39	1.78	0.076
Clarity[Blurred] x Condition [Far]	-0.003	0.004	130.04	-0.70	0.483
Clarity[Blurred] x Condition [Mid]	-0.019	0.004	133.01	-4.75	<.001
Log_{10}[Trial]	-0.154	0.014	43.99	-11.32	<.001

Note. Model was performed using effect coding [(Clarity: 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.

Table 6 displays the Log_{10}(RT) *M* with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for *Clarity* x *Condition* in msec. Figure 9 shows the Log_{10}(RT) *M* and *SEM* for

[3] The two other models were Raw(RT) ~ Clarity + Condition + Clarity x Condition + (Clarity + Condition + Clarity x Condition|Participant) with R^2 = .21, adjusted R^2 = .21, RMSE = 335.85 [no BIC because Raw(RT) instead of Log(RT)], and Log(RT) ~ Clarity + Condition + Clarity x Condition (Clarity + Condition + Clarity x Condition|Participant) with R^2 = .28, adjusted R^2 = .28, RMSE = 0.13, BIC = -2963.6.

Clarity x *Condition* in msec with RT* as a secondary y-axis. The linear multilevel model, Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) was analyzed for significant main effects and an interaction. There was a significant main effect for Log_{10}(Trial), $F(1, 44.0) = 128.20$, $p < .001$, indicating that participants responded faster as they progressed through the experiment. Importantly, there was not a significant main effect for *Clarity*, $F(1, 52.7) = 0.17$, $p = .680$, suggesting that blurred and clear conditions were responded to at a similar rate. However, there were significant differences for *Condition*, $F(3, 156.4) = 11.30$, $p < .001$, and most importantly for the interaction between *Clarity* x *Condition*, $F(3, 170.8) = 8.63$, $p < .001$, which is further investigated with post hoc comparisons using the Tukey HSD test (see Table 7). The exact nature of this interaction allows us to test between the three alternative competing hypotheses shown in Figure 2.

Table 6

Clarity x Condition: Log_{10}(RT) M with SD and RT GM with GSDs*

Clarity	Condition	Log_{10}(RT) M	Log_{10}(RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
Blurred	All	2.873	0.121	747	566	986
Blurred	Far	2.867	0.127	736	550	985
Blurred	Mid	2.866	0.122	734	554	973
Blurred	Target	2.862	0.103	728	574	923
Clear	All	2.846	0.104	702	553	891
Clear	Far	2.867	0.126	737	551	985
Clear	Mid	2.908	0.140	809	586	1117
Clear	Target	2.831	0.112	677	523	877

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 7

Tukey HSD Comparisons for Clarity x Condition Interaction with $Log_{10}(RT)$

Level (Clarity x Condition)	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Clear,Mid	A	2.90	0.012	2.872	2.921
Clear,Far	AB	2.87	0.012	2.848	2.896
Blurred,All	AB	2.87	0.013	2.844	2.896
Blurred,Far	B	2.87	0.012	2.845	2.893
Blurred,Mid	B	2.86	0.012	2.837	2.885
Blurred,Target	BC	2.86	0.013	2.832	2.883
Clear,All	BC	2.85	0.013	2.825	2.877
Clear,Target	C	2.83	0.013	2.803	2.854

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, $Q = 3.07$).

As shown in Table 7 and Figure 9, the all-blurred and all-clear conditions were not significantly different, suggesting legibility was controlled. This was as predicted, because when unique clarity/blur is absent then there would be a lack of guidance for selective attention, producing random search. The all-blurred and all-clear conditions therefore serve as the baseline for the singleton conditions that may influence selective attention. Comparing Figure 2 with Figure 9, there is strong evidence in support of the Blur Ignored hypothesis. Importantly, the blurred target condition did not significantly differ from any of the other blur conditions. Conversely, the all-clear condition did not significantly differ from the clear target and far distractor singleton conditions, but did significantly differ from the mid distractor condition. Nevertheless, the clear target singleton did significantly differ from both clear distractor conditions. The results are therefore providing some support for both clarity capturing and being ignored by selective attention. The blurred and clear target singletons did not significantly differ, suggesting they have similar influences on selective attention, thus providing some support for the blur captures hypothesis. However, because both target singleton conditions did not differ from their respective *all-(blurred/clear)* conditions, the results can also be interpreted as neither unique clarity nor unique blur guiding selective attention, which is most consistent with the Blur Ignored hypothesis. Thus, it appears that the manipulation was not strong enough or lacked the necessary power for the analyses. However, based only on the blur conditions, which is critical for distinguishing between the three hypotheses (see Figure 2), the Blur Ignored hypothesis is most strongly supported.

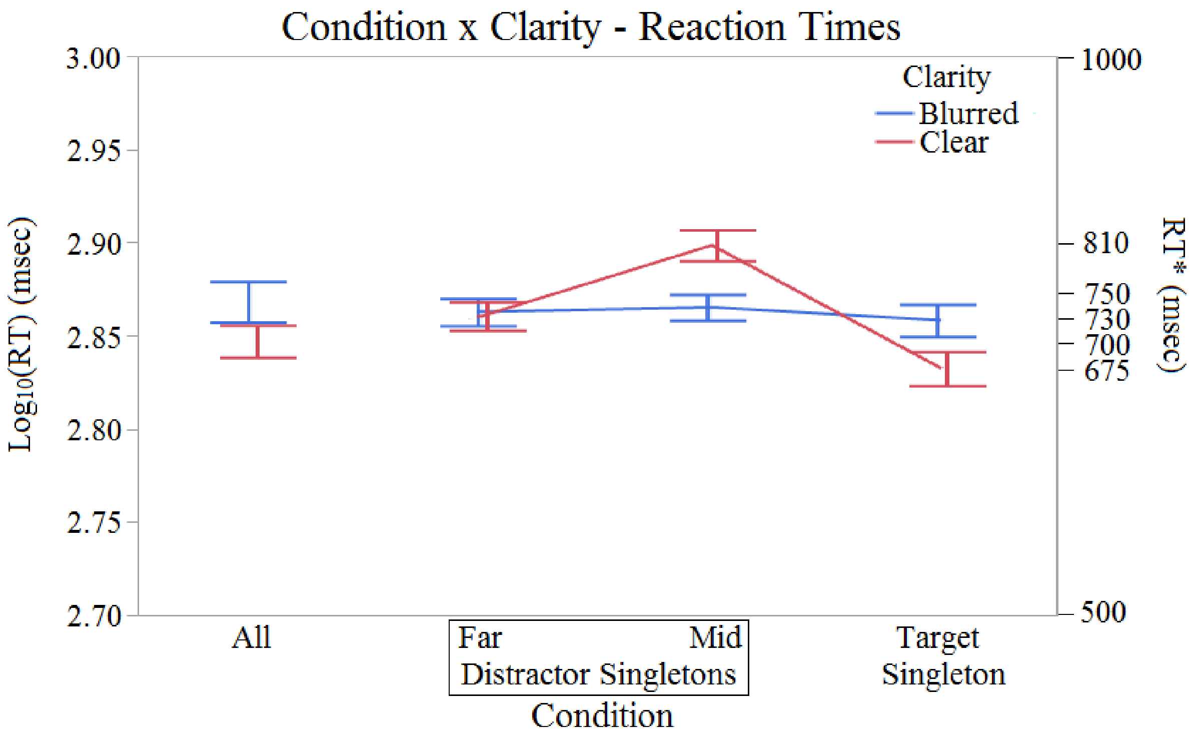

Figure 9. The Log_{10}(RT) *M* for *Condition* x *Clarity* with +/- 1 SEM bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale.

Three models, one for each predicted hypothesis, were used to test which hypothesis explained the data best using linear multilevel modeling. Each model had a similar structure such that Log_{10}(RT) was predicted by the main effects of one of the quantitative prediction hypotheses with Log_{10}(Trial). The slopes of the quantitative prediction hypothesis selected with the Log_{10}(Trial) were then also allowed to vary across each participant. Table 8 displays the parameter estimates for the best model. All three models had the same R^2 = .45, adjusted R^2 = .45, RMSE = 0.12, but differ based on BIC values. BIC values that differ from 2-4 points can be accepted as moderate support for the lower model being the better model, while a difference of ~7 is strong and 10+ is very strong evidence that the lower model can be accepted as the better model and reject the model with the higher BIC value. The best model was with Blur Ignored, BIC = -3715.3, which is 15.7 points lower and thus strongly accepted as the better model compared to Blur Captures, BIC = -3699.6, and is even more strongly accepted than Blur Repels, BIC = -3689.1. Likelihood ratios reveal that Blur Ignored is 2,566 and 488,942 times more likely to have produced the observed reaction times compared to the Blur Captures and Blur Repels hypotheses, respectively.

Table 8

Parameter Estimates $Log_{10}(RT)$ ~ Hypothesis (Blur Ignored) + $Log_{10}(Trial)$ + (Hypothesis (Blur Ignored) + $Log_{10}(Trial)$|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	3.128	0.032	66.17	97.04	<.001
Hypothesis 3 - Blur Ignored	0.022	0.003	56.04	6.94	<.001
Log_{10}(Trial)	-0.155	0.014	44.35	-11.24	<.001

Note. DFDen = degrees of freedom used in the denominator.

Discussion

The results from Experiment 1 suggest that the pilot control study was successful at obtaining a level of blur that was equally legible whether presented clearly or blurred. This is based on the all-blurred and all-clear conditions not being significantly different from one another. This result also suggests that when all letters were presented in the same level of *Clarity* a random search was performed to find the target without guidance.

The main findings were that none of the blurred conditions differed from one another, while the clear target singleton was responded to faster than the clear distractor singletons, but not the all-clear condition. Other than the clear target singleton not being significantly faster than the all-clear condition, this is exactly what the Blur Ignored hypothesis predicts, which was also the most supported hypothesis based on the model analyses across all three predicted hypotheses.

The three prediction hypotheses' most obvious difference is between the clear and blurred target singleton conditions and how they differ from their respective *all-(blurred/clear)* conditions. The Blur Repels hypothesis was not supported because the blur target singleton was not statistically slower in RT from either the clear target singleton or the all-blurred conditions, both of which would be predicted to differ from it, as shown in Figure 2. The Blur Captures hypothesis had some support based mostly on the blurred and clear target singletons not significantly differing in RTs, as predicted in Figure 2. While the clear and blurred target singletons did not significantly differ from the all-clear and all-blurred conditions, there did appear to be a general trend toward clear singleton capture, as shown in Figure 9.

The above raises some questions that were further investigated in Experiment 2. Specifically, the key issue was whether the clear and blurred target singletons are either capturing or not influencing selective attention. A plausible approach to clarifying this issue is to amplify the difficulty of the search task, which should make any type of attentional guidance more apparent in the RT data.

Chapter 4 - Pilot Experiment 2

Method

As with Pilot Experiment 1, we carried out Pilot Experiment 2 in order to control for legibility issues after changing the letter stimuli to have the L distractors appear more T-like. Again, the blurred and clear letters had similar accuracy and reaction times, thus, similarly to Experiment 1, allowing Experiment 2's results to be interpreted as changes in attention, not difficulty identifying the blurred letters.

Participants

There were 32 participants from Kansas State University's (KSU) undergraduate research pool (24 females, mean age = 18.5). Participants' vision was tested and was 20/30 or better. All participants were naïve at the beginning of the pilot. All participants gave their informed consent and participated for class credit.

Apparatus and Stimuli

All apparatus was the same as in the Experiment 1 pilot study. As shown in Figure 10, the stimuli were changed to make the L distractors appear more T-like (Jiang & Chun, 2001). The clear L and T images' vertical and horizontal lines were 44 pixels (1.65° of visual angle) in length. Both lines have a width of 4 pixels (0.15° of visual angle). The images were blurred using the same methods as explained in the Experiment 1 pilot study. There are two set sizes (4 & 8) for Experiment 2, and the locations of the letters for both set sizes did not overlap, resulting in 12 potential locations along a centered invisible circle set to a radius of 9° degrees of visual angle. When the set size was four, the images appeared from the top of the circle at 22.5°, 112.5°, 202.5°, and 292.5°. When the set size was eight, the images appeared from the top of the circle at 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°.

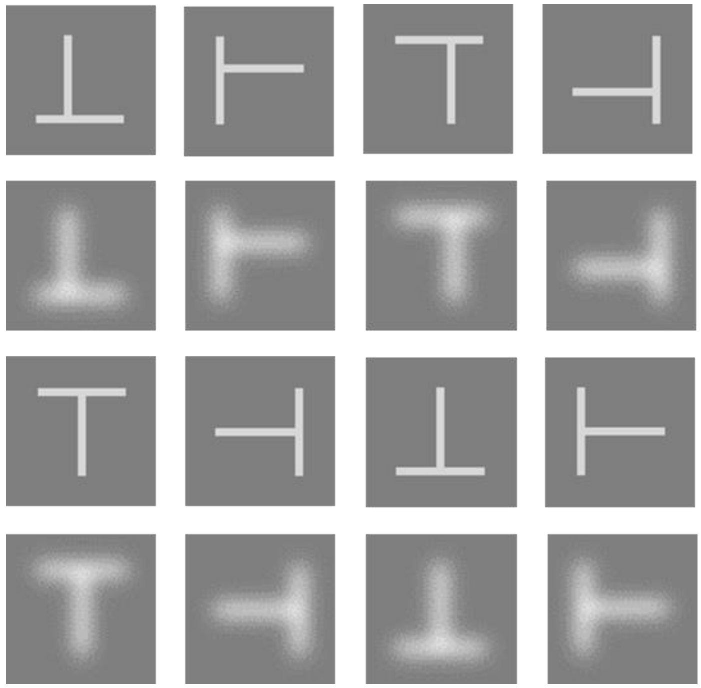

Figure 10. Images of the L and T blurred/clear letter rotations. Row 1 clear L rotated (0, 90, 180, and 270). Row 2 blurred L with same rotations. Row 3 clear T with same rotations as the Ls. Row 4 displays the blurred Ts with the same rotations as above.

Design

The experimental design was identical to Experiment 1's pilot study. There was a 2 (Letter: L vs. T) x 2 (Clarity: Clear vs. Blurred) within-subjects design. The counterbalancing of *Letter*, *Clarity*, and the 12 potential locations a letter could be presented at, resulted in 48 trials per block, and six blocks, resulting in 288 total trials. All 288 trials were then randomized across each participant's experimental session. The dependent variables were accuracy for the identification task and RT.

Procedure

Participants first read and gave their informed consent, then their visual acuity was tested using the Freiburg Visual Acuity and Contrast Test (FrACT) (Bach, 1996; Bach, 2007). Participants then read instructions to the experiment. This was then followed by another instruction screen showing the participants examples of what the T targets looked like presented clearly and blurred as well as the L distractors. The trials began by having the participants observe a fixation cross at the center of the screen. Once their eyes were focused on the middle of the fixation cross they hit the next button on the response pad. The fixation cross was then removed from the screen and a blank neutral gray screen was presented for 506 msec followed by the presentation of a single L or T letter which remained present until a response was made. There was no response screen that appeared. Once the participant had pushed the left response button to indicate they saw an L, or the right response button to indicate they saw a T, there was a blank neutral gray screen presented for 1000 msec, before the next trial. Participants were allowed to quit or take a break at any time during the experiment; also every 72 trials the participants received a built in mandatory break with a total of 288 trials. After finishing the experiment, participants read through a debriefing form and were then thanked for their participation.

Pilot Experiment 2 Results

The analyses were conducted on 32 participants, however prior to the analyses, data from nine other participants were lost due to computer error in recording the participants' results. Prior to cleaning any of the data, the overall accuracy across all trials was 95%. The data was then cleaned by first removing all reaction times < 150 msec or > 10 seconds. This resulted in 13 trials being removed from 9216 trials (0.1% of all trials).

The analyses of accuracy were conducted with the R statistical software (version x64 3.1.1) to run a multilevel logistic regression for binary data. Prior to analyzing the models, the categorical variables *Letter* and *Clarity* were effect coded such that Letter (L = +1, T = -1) and Clarity (Blurred = +1, Clear = -1). Table 9 displays the parameter estimates for the fixed effects and random effects variance from the best model. From the analyses, the best model was Accuracy ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (1|Participant) (BIC = 3370.5) compared to the second best model which included the random effect of (Letter|Participant) (BIC = 3377.6) (See Appendix D for all models with BIC values).

Table 9

Parameter Estimates for Accuracy ~ Letter + Clarity + Letter x Clarity + Log$_{10}$(Trial) + (1|Participant) Model

Fixed Effects	Estimates	Std Error	z-value	p(z)	Random Effects Variance
Intercept	3.521	0.317	11.11	<.001	1.201
Letter(L)	-0.048	0.049	-0.98	0.325	
Clarity(Blurred)	0.051	0.049	1.05	0.294	
Log$_{10}$(Trial)	-0.045	0.118	-0.38	0.705	
Letter(L) x Clarity(Blurred)	0.066	0.049	1.36	0.174	

Note. Model was performed using effect coding [(Letter: L = +1, T = -1) (Clarity: Blurred = +1, Clear = -1)].

Figure 11 displays the mean transformed accuracy values back to proportion from logit space for the clear and blurred Ls and Ts at the end of the experiment. There were no significant main effects or interactions for *Letter* or *Clarity*. Most importantly, this suggests that level of *Clarity* had no influence on accuracy in identifying the letters.

Figure 11. The mean accuracy for each letter presented clearly or blurred. Error bars = 95% CI after being transformed back from logit, therefore the error bars are asymmetrical, having slightly longer negative error bars.

Prior to analyzing the data for reaction times there was further cleaning of the data such that all of the incorrect responses were removed. From the 9203 total trials, 461 trials were removed due to being incorrect responses (5% of trials).

The analyses were conducted using a linear multilevel model with effect coding in JMP Pro 12. Table 10 displays the parameter estimates for the model. The model analyzed was the same as Experiment 1 pilot study, Log_{10}(RT) ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (Letter + Clarity + Letter x Clarity + Log_{10}(Trial)|Participant) with $R^2 = .23$, adjusted $R^2 = .22$, RMSE = 0.12.

Table 10

Parameter Estimates from Log_{10}(RT) ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (Letter + Clarity + Letter x Clarity + Log_{10}(Trial)|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	2.991	0.020	46.31	147.53	<.001
Letter(L)	0.003	0.003	31.08	1.05	0.301
Clarity(Blurred)	-0.001	0.002	29.04	-0.87	0.391
Letter(L) x Clarity(Blurred)	-0.005	0.002	31.25	-3.24	0.003
Log_{10}(Trial)	-0.062	0.009	30.66	-7.04	<.001

Note. Model was performed using effect coding [(Letter: L = +1, T = -1)(Clarity: Blurred = +1, Clear = -1)]. DFDen = degrees of freedom used in the denominator.

Table 11 presents the Log_{10}(RT) *M* with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for the clear and blurred Ls and Ts in msec. Figure 12 displays the Log_{10}(RT) *M* and *SEM* for *Clarity* x *Letter* in msec with RT* *GM* on secondary y-axis. As in the Experiment 1 pilot study, the linear multilevel model, Log_{10}(RT) ~ Letter + Clarity + Letter x Clarity + Log_{10}(Trial) + (Letter + Clarity + Letter x Clarity + Log_{10}(Trial)|Participant) was analyzed for significant main effects and an interaction. There was a significant main effect for Log_{10}(Trial), $F(1, 30.7) = 49.61$, $p <.001$, indicating that participants responded faster as they progressed through the experiment. There was no significant main effect for Letter, $F(1, 31.1) = 1.11$, $p = .301$, with Ls identified at similar rates to Ts. There was no significant main effect for Clarity, $F(1, 29.0) = 0.76$, $p = .391$, indicating blurred and clear letters are identified at similar rates. There was a significant interaction effect between Letter x Clarity, $F(1, 31.25) = 10.47$, $p =.003$, therefore one letter was identified faster or slower than at least one of the letters at a *specific Clarity* level.

Table 11

Letter x Clarity: Log_{10}(RT) M with SD and RT GM with GSDs*

Letter	Clarity	Log_{10}(RT) M	Log_{10}(RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
L	Blurred	2.863	0.116	729	558	952
L	Clear	2.875	0.113	749	577	972
T	Blurred	2.866	0.124	734	551	977
T	Clear	2.857	0.119	720	548	947

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.

Two planned contrasts compared the RTs for the levels of *Clarity* for each *Letter*. The first contrast found a significant difference between the RTs for clear and blurred Ls, $t(31.25) = 2.92$, $p = .005$, with the blurred Ls slightly faster. The second contrast found no significant difference in RT between the clear and blurred Ts, $t(31.25) = 1.70$, $p = .094$. These results showed there was no significant accuracy difference between the Ls and Ts. Clear and blurred Ls did significantly differ on Log_{10}(RT) with the blurred Ls being responded to *faster* than the clear Ls. Importantly, the blurred and clear Ts did not significantly differ (14 msec). This is important because in Experiment 2, only the Ts were used as the target for each search. Also, while the Ls did significantly differ, they differed by 20 msec. This difference should have a very minimal effect on the results for Experiment 2 with Ls being distractors. Therefore, legibility was controlled for between the clear and blurred letters. Results from Experiment 2 should not be based on whether or not a blurred target was harder to identify than a clear target.

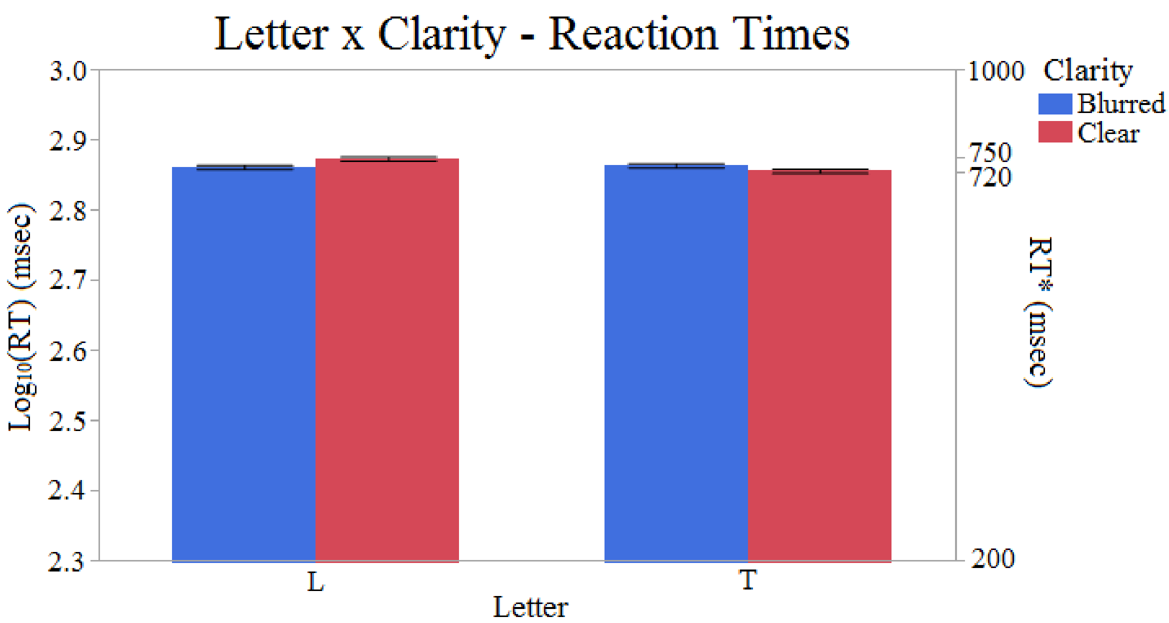

Figure 12. The Log_{10}(RT) marginal means for each letter presented clearly or blurred with +/- 1 SEM bars. RT* GMs are also presented on the secondary y-axis.

Chapter 5 - Experiment 2

Method

Several changes were made to Experiment 2 in order to amplify the effect blur and clarity might have on selective attention. In general, more difficult tasks require more attention. Thus, in Experiment 2, there are two set sizes (4 & 8), given that set size is a fundamental variable used to manipulate task difficulty in visual search paradigms. Similarly, the L distractors were made to look more T-like to further increase the task difficulty. The letters were moved further into the visual periphery to 9° eccentricity, which allowed them to maintain reasonable inter-item distance, but also served to make the task more difficult. Finally, the task was changed to indicate the direction the target was pointing (left vs. right pointing T), thus allowing a target to be present on every trial. This allowed for greater statistical power with fewer trials than in Experiment 1.

Participants

There were 53 participants from Kansas State University's (KSU) undergraduate research pool (30 females, mean age = 19.6). Participants' vision was tested and was 20/30 or better. All participants were naïve at the beginning of the experiment. All participants gave their informed consent and participated for class credit.

Apparatus and Stimuli

All the apparatus was the same as the previous studies. The same letter images from the Experiment 2 pilot study were used here. Figure 13 displays the two set sizes (4 & 8), and both placed the letters around the same invisible circle set to a radius of 9° degrees of visual angle as the Experiment 2 pilot study. The set size of four letters had a Bouma's constant of 1.21, while the set size of eight letters had a Bouma's constant of 0.58 indicating that crowding should not have influenced either set size during the search task (Bouma, 1970). To increase participants' accuracy, participants also completed *accuracy cards* (Appendix E). The accuracy cards asked participants to write their name on the card and fill out their cumulative accuracy score at each mandatory break and at the end of the experiment, and then turn them in to the experimenter at the end of the experiment. This was done to increase participants' level of effort, thus allowing more of their RT data to be analyzed.

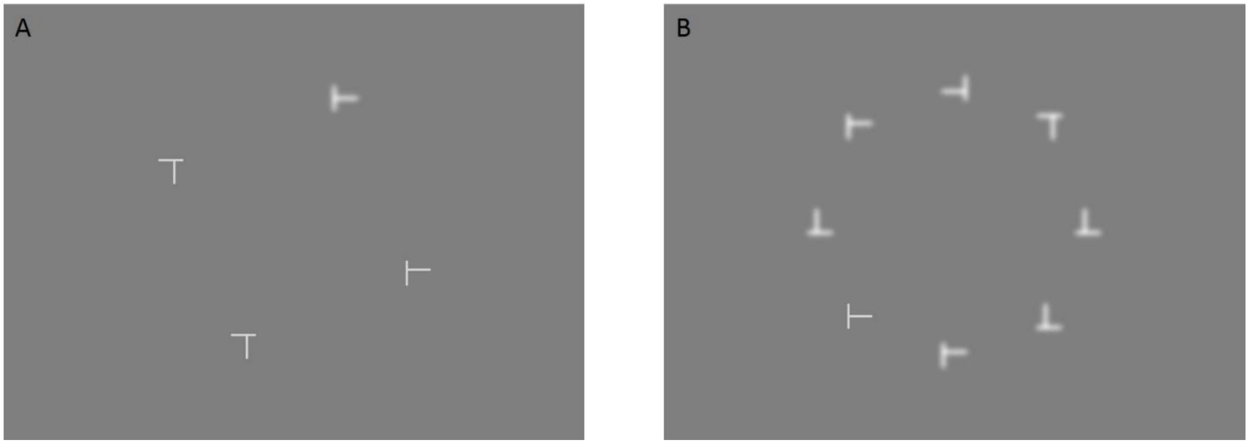

Figure 13. A) Example set size of four, Blurred Target Singleton, and B) set size of eight, Clear Target Singleton example.

Design

The rotated L and T visual search was a within-subject design based on two set sizes. The set size of four was a 2 (Clarity: Blur vs. Clear) x 4 (Condition: All, Far, Mid, & Target) design. The set size of eight was a 2 (Clarity: Blur vs. Clear) x 6 (Condition: All, Far, Far-Mid, Mid, Near, & Target) design. All participants completed both set sizes, which were counterbalanced such that the first or last 80 trials were the set size of four trials, while the remaining 288 trials were for the set size of eight, for a total of 368 trials. The difference in the number of trials for the set sizes of four and eight is explained below.

Within the set size of four, the trials were counterbalanced for target orientation (left vs. right), target clarity (blur vs. clear), and target location (1 of 4 locations). Nested within each of these targets are five permutations of the three distractors' clarity (blur vs. clear). The five permutations are made up from the All, Target Singleton, and three Distractor Singleton conditions (1 Far & 2 Mid). The rotation of the letters was randomized on each trial.

Within the set size of eight, the trials were counterbalanced for target orientation (left vs. right), target clarity (blur vs. clear), and target location (1 of 8 locations). Nested within each of these targets are nine permutations of the seven distractors' clarity (blur vs. clear). The nine permutations are made up from the All, Target Singleton, and seven Distractor Singleton conditions (2 Near, 2 Mid, 2 Far-Mid, & 1 Far). The rotation of the letters was randomized on each trial. The dependent variable was correct trial RT for the target orientation task. Because of the different set sizes, the number of trials required to counterbalance the targets' clarity, orientation, and location, as well as keeping *Clarity* non-predictive of target location, there were 288 trials in the set size of eight versus 80 trials for the set size of four.

Procedure

Participants first read and gave their informed consent, then their visual acuity was tested using the Freiburg Visual Acuity and Contrast Test (FrACT) (Bach, 1996; Bach, 2007). The experiment started with an instruction screen to inform the participants how to complete their task and fill out their accuracy score cards. Figure 14 shows a trial schematic.

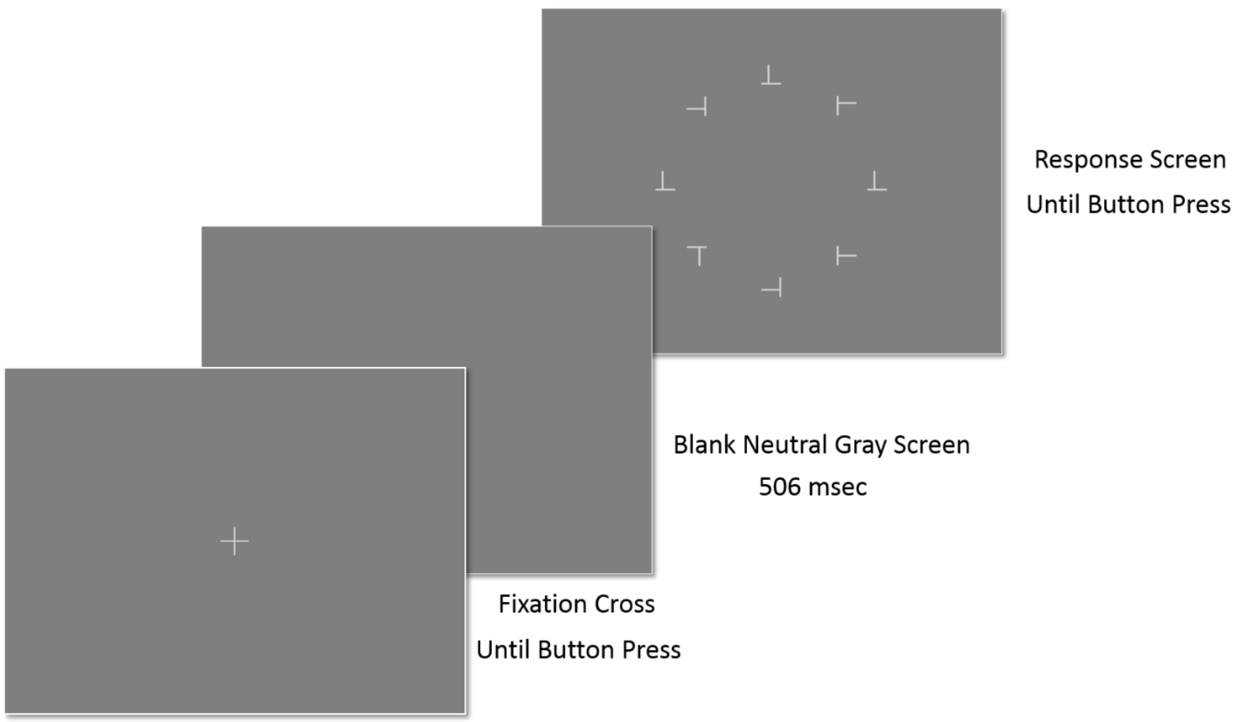

Figure 14. Trial schematic.

As shown in Figure 14 trial schematic, the participants saw a fixation cross at the center of the screen and hit the "NEXT" button on the response pad to begin the trial. A blank neutral gray screen was presented for 506 msec, followed by the letters either as a set size of four or eight, which remained present until the participant pushed either the left (T pointing left) or right (T pointing right) response button on the response pad. A feedback screen was shown informing them whether they were correct or incorrect for 1000 msec. Participants were allowed to quit or take a break at any time during the experiment, and every 92 trials the participants took a mandatory break. There were a total of 368 trials. At each break screen, participants were given additional feedback by being shown their current cumulative accuracy percentage. If accuracy was < 80%, then the participants were encouraged to "Try harder"; if > 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 turned in their accuracy cards to the experimenter. They were then thanked for their participation.

Experiment 2 Results

The analyses were conducted on 53 participants, however prior to the analyses three other participants were excluded for having accuracy scores < 60%. Prior to cleaning the data, the overall accuracy across all trials was 90%. The data were then cleaned, removing all reaction times that were < 150 msec or > 10 seconds (120 trials), and incorrect responses (1862 trials). Overall, 1982 trials were removed from 19504, resulting in 10% of all the data trials being removed.

The following analyses were all completed using Log_{10}(RT). The data was collected using two set sizes (4 & 8). A linear multilevel model with effect coding in JMP Pro 12 was performed to determine if there was a main effect for Set Size. The model was Log_{10}(RT) was predicted by Set Size and Log_{10}(Trial) as main effects. The slopes of the Set Size and Log_{10}(Trial) were also allowed to vary across participants. The model had an R^2 = .26, adjusted R^2 = .26, RMSE = 0.22. There was a significant main effect for set size, $F(1, 50.9) = 320.61$, p <.001. Therefore, all following analyses are conducted split by the two set sizes.

Set Size 4 Analyses:

As in Experiment 1, the following analyses were all completed using Log_{10}(RT). Three linear multilevel models with effect coding in JMP Pro 12 were performed to determine the best approach at explaining the variance within the data. Table 12 displays the parameter estimates for the best model analyzed, which was the same structure as in Experiment 1, Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x

Condition+ Log_{10}(Trial)|Participant) with R^2 = .38, adjusted R^2 = .38, RMSE = 0.16, BIC = -2635.3.[4]

Table 12

Parameter Estimates from the Set Size 4: Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	3.448	0.036	36.00	95.99	<.001
Clarity[Blurred]	0.004	0.002	59.04	1.56	0.124
Condition[All]	0.009	0.005	191.48	1.92	0.057
Condition[Far]	-0.004	0.005	195.97	-0.78	0.435
Condition[Mid]	0.014	0.004	80.92	3.47	0.001
Clarity[Blurred] x Condition[All]	-0.001	0.006	186.21	-0.09	0.928
Clarity[Blurred] x Condition[Far]	-0.015	0.006	189.87	-2.57	0.011
Clarity[Blurred] x Condition[Mid]	-0.009	0.005	102.15	-1.76	0.082
Log_{10}[Trial]	-0.147	0.015	29.80	-9.77	<.001

Note. Model was performed using effect coding [(Clarity; 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.

Table 13 displays the Log_{10}(RT) *M* with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for *Clarity* x *Condition* in msec. Figure 15 shows the Log_{10}(RT) *M* and *SEM* for *Clarity* x *Condition* in msec with RT* as a secondary y-axis. The linear multilevel model, Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) was analyzed, and results were the same as found in Experiment 1. Participants made quicker responses as they moved through the experiment, Log_{10}(Trial), $F(1, 29.8) = 95.55$, $p <.001$. There was no significant main effect for *Clarity*, $F(1, 59.0) = 2.44$, $p = .124$, indicating that, overall, the blur and clear conditions had similar rates of response, supporting legibility being controlled. Again, both *Condition* had a significant main effect, $F(3, 141.9) = 8.13$, $p < .001$, and the interaction of *Clarity* x *Condition*, $F(3, 154.0)$ =

[4] The two other models were Raw(RT) ~ Clarity + Condition + Clarity x Condition + (Clarity + Condition + Clarity x Condition|Participant) with R^2 = .27, adjusted R^2 = .27, RMSE = 731.03 [no BIC because Raw(RT) instead of Log(RT)], and Log(RT) ~ Clarity + Condition + Clarity x Condition + (Clarity + Condition + Clarity x Condition|Participant) with R^2 = .33, adjusted R^2 = .33, RMSE = 0.17, BIC = -2392.1.

6.69, $p < .001$, which is further investigated with post hoc comparisons using the Tukey HSD test (see Table 14). As in Experiment 1, the nature of this interaction is what allows us to test between the three alternative competing hypotheses shown in Figure 2.

Table 13

Clarity x Condition: Log_{10}(RT) M with SD and RT GM with GSDs*

Clarity	Condition	Log_{10}(RT) M	Log_{10}(RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
Blurred	All	3.163	0.167	1456	992	2138
Blurred	Far	3.142	0.163	1388	953	2020
Blurred	Mid	3.163	0.173	1456	977	2170
Blurred	Target	3.161	0.150	1449	1026	2046
Clear	All	3.162	0.163	1453	998	2114
Clear	Far	3.161	0.153	1450	1020	2059
Clear	Mid	3.170	0.159	1479	1025	2133
Clear	Target	3.109	0.181	1285	848	1949

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 14

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

Level (Clarity x Condition)	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Clear,Mid	A	3.17	0.017	3.139	3.206
Blurred,All	AB	3.17	0.018	3.131	3.201
Blurred,Mid	AB	3.16	0.017	3.129	3.196
Blurred,Target	AB	3.16	0.018	3.127	3.197
Clear,Far	AB	3.16	0.018	3.126	3.196
Clear,All	AB	3.16	0.018	3.125	3.195
Blurred,Far	BC	3.14	0.018	3.103	3.174
Clear,Target	C	3.11	0.018	3.072	3.142

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, $Q = 3.07$).

As shown in Table 14 and Figure 15, and replicating Experiment 1, the all-blurred and all-clear conditions were not significantly different, thus showing that blurring the letters did not alter the search for the T target based on legibility. This finding also further supports the idea that random search occurs in the absence of a unique blurred or clear letter to possibly influence selective attention. Thus, the all-blurred and all-clear conditions again serve as the baseline for the singleton conditions that may influence selective attention. As can be seen by comparing Figure 2 with Figure 15, there is strong support for the Blur Ignored hypothesis. First, we replicated the finding from Experiment 1 that none of the blur conditions significantly differed from one another, suggesting selective attention ignores unique blur. Importantly, the clear target singleton was responded to faster than any other clear conditions, providing stronger evidence than in Experiment 1 that clarity captured attention to its spatial location. However, being captured to a distractor appeared to have little effect on the reaction time, while being captured to the target did. Most importantly, the blurred and clear target singletons did significantly differ, which was not found in Experiment 1; unique clarity captured selective attention while unique blur had longer RTs that were similar to the all-blurred condition, and thus did not capture attention. Overall, these results mostly support the hypothesis that blur is ignored by selective attention while unique clarity captures attention.

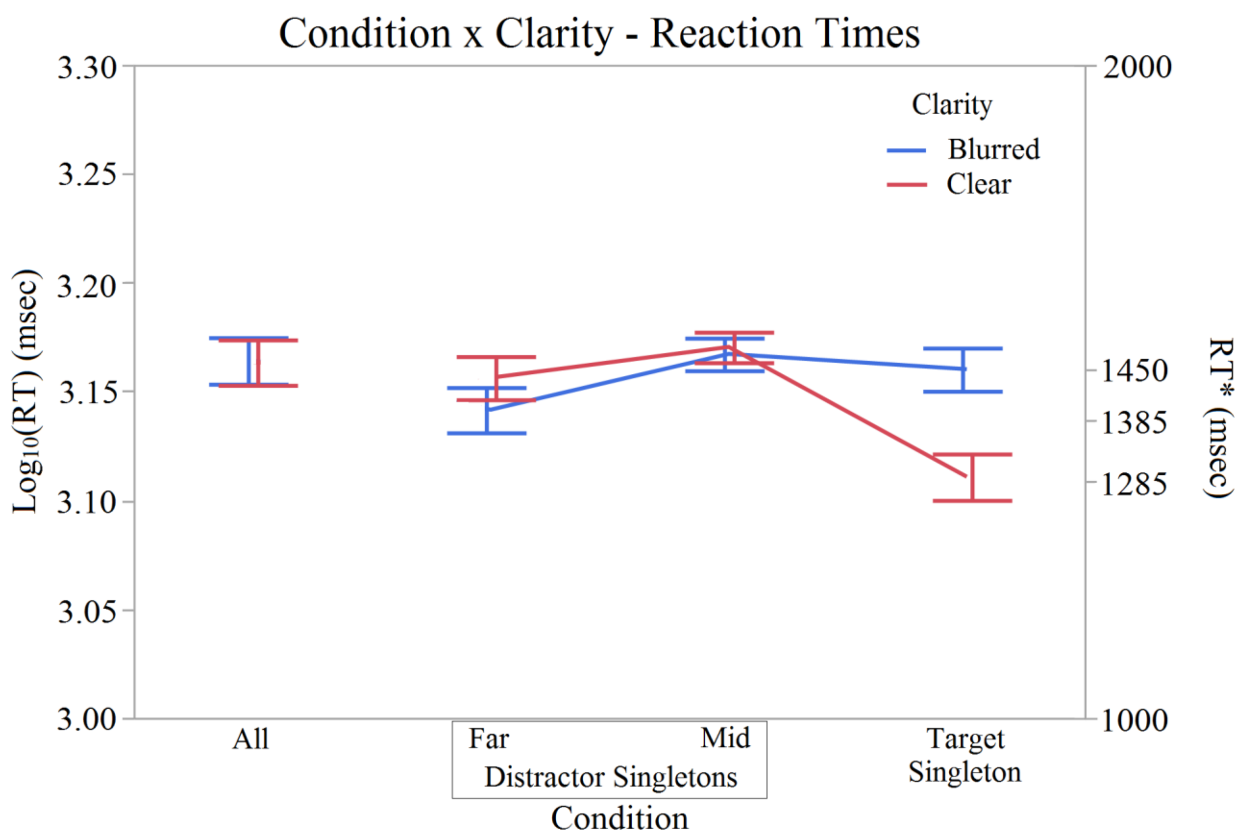

Figure 15. The Log_{10}(RT) *M* for *Condition* x *Clarity* with +/- 1 SEM bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale.

As in Experiment 1, a model for each quantitatively predicted hypothesis was compared using linear multilevel modeling. Each model had a similar structure to that in Experiment 1. The Blurred Ignored and Blur Repels hypotheses' models both had the same R^2 = .38, adjusted R^2 = .38, and RMSE = 0.16, however Blur Captures slightly differed with R^2 = .37, adjusted R^2 = .36, and RMSE = 0.17. The main difference between the models was again in their BIC values, which strongly supports that Blur Ignored (BIC = -2746.6) is the better model, being 7.6 points lower than the Blur Repels model (BIC = -2739.0) and 35.8 points lower than the Blur Captures model (BIC = -2710.8). Table 15 displays the parameter estimates for the Blur Ignored model. The likelihood ratios show that Blur Ignored is 45 and 59,411,597 times more likely to have produced the reaction times than the Blur Repels and Blur Captures hypotheses, respectively.

Table 15

Parameter Estimates Log_{10}(RT) ~ Hypothesis (Blur Ignored) + Log_{10}(Trial) + (Hypothesis (Blur Ignored) + Log_{10}(Trial)|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	3.374	0.039	50.82	86.88	<.001
Hypothesis 3 - Blur Ignored	0.031	0.006	51.75	4.82	<.001
Log_{10}(Trial)	-0.147	0.015	29.91	-9.86	<.001

Note. DFDen = degrees of freedom used in the denominator.

Set Size 8 Analyses:

As in Experiment 1 and Experiment 2's set size of four, the following analyses are all completed using Log_{10}(RT). Three linear multilevel models were effect coded in JMP Pro 12 to determine the best model, which again was Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) with R^2 = .21, adjusted R^2 = .21, RMSE = 0.23, BIC = -1097.6.[5] Table 16 displays the parameter estimates for the best model analyzed.

[5] The two other models were Raw(RT) ~ Clarity + Condition + Clarity x Condition + (Clarity + Condition + Clarity x Condition|Participant) with R^2 = .14, adjusted R^2 = .13, RMSE = 1354.36 [no BIC because Raw(RT) instead of Log(RT)], and Log(RT) ~ Clarity + Condition + Clarity x Condition + (Clarity + Condition + Clarity x Condition|Participant) with R^2 = .15, adjusted R^2 = .15, RMSE = 0.23, BIC = -450.8.

Table 16

Parameter Estimates from the Set Size 8: Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	3.619	0.072	51.16	50.38	<.001
Clarity[Blurred]	0.004	0.002	53.91	1.90	0.062
Condition[All]	0.008	0.005	463.34	1.43	0.153
Condition[Far]	0.016	0.005	452.76	3.06	0.002
Condition[Far-Mid]	0.022	0.004	168.72	5.40	<.001
Condition[Mid]	0.017	0.004	167.08	4.02	<.001
Condition[Near]	-0.008	0.004	166.92	-2.00	0.047
Clarity[Blurred] x Condition[All]	-0.006	0.006	341.90	-0.98	0.330
Clarity[Blurred] x Condition[Far]	-0.012	0.006	334.38	-1.99	0.048
Clarity[Blurred] x Condition[Far-Mid]	-0.011	0.005	167.23	-2.16	0.032
Clarity[Blurred] x Condition[Mid]	-0.003	0.005	165.52	-0.51	0.610
Clarity[Blurred] x Condition[Near]	-0.011	0.005	165.69	-2.11	0.036
Log_{10}[Trial]	-0.130	0.032	47.24	-4.06	<.001

Note. Model was performed using effect coding [(Clarity: 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. VIF = variance inflation factor.

Table 17 displays the Log_{10}(RT) *M* with within-subject *SD*, and the RT* *GM* with within-subject *GSD* for *Clarity* x *Condition* in msec. Figure 16 shows the Log_{10}(RT) *M* and *SEM* for *Clarity* x *Condition* in msec with RT* as a secondary y-axis. The linear multilevel model, Log_{10}(RT) ~ Clarity + Condition + Clarity x Condition + Log_{10}(Trial) + (Clarity + Condition + Clarity x Condition + Log_{10}(Trial)|Participant) was analyzed for significant main effects and an interaction. The findings replicated both Experiment 1 and Experiment 2's set size of four results with a significant main effect for Log_{10}(Trial), $F(1, 47.2) = 16.46$, $p <.001$, indicating that participants responded faster as they progressed through the experiment. Again, there was no significant main effect for Clarity, $F(1, 53.9) = 3.62$, $p = .062$, providing evidence for blurred letters' legibility not being an issue as the two *Clarity* conditions were responded to at similar rates. Also, there was a significant difference between the *Condition* conditions $F(5, 244.6) = 27.40$, $p < .001$, signifying at least one difference between All, Far, Far-Mid, Mid, Near, and Target. Once more there was a significant interaction for *Clarity* x *Condition*, $F(5, 222.4) =$

10.31, $p < .001$, which was further investigated with post hoc comparisons using the Tukey HSD test (see Table 18). Importantly, the nature of this interaction allows us to test the three alternative competing hypotheses shown in Figure 2.

Table 17

Clarity x Condition: Log$_{10}$(RT) M with SD and RT GM with GSDs*

Clarity	Condition	Log$_{10}$(RT) M	Log$_{10}$(RT) SD	RT* GM	RT* -1 GSD	RT* +1 GSD
Blurred	All	3.340	0.223	2188	1309	3657
Blurred	Far	3.333	0.227	2153	1275	3633
Blurred	Far-Mid	3.341	0.231	2193	1289	3732
Blurred	Mid	3.344	0.233	2210	1293	3779
Blurred	Near	3.313	0.242	2054	1176	3587
Blurred	Target	3.319	0.214	2084	1272	3414
Clear	All	3.341	0.233	2194	1283	3752
Clear	Far	3.352	0.229	2251	1328	3814
Clear	Far-Mid	3.356	0.222	2272	1364	3784
Clear	Mid	3.341	0.231	2195	1289	3738
Clear	Near	3.328	0.228	2129	1258	3603
Clear	Target	3.229	0.240	1693	975	2939

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 18

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

Level (Clarity x Condition)	Letters	Least Sq Mean	Std Error	Lower 95%	Upper 95%
Clear,Far-Mid	A	3.36	0.015	3.333	3.393
Clear,Far	AB	3.36	0.016	3.326	3.390
Blurred,Mid	AB	3.35	0.015	3.322	3.382
Blurred,Far-Mid	ABC	3.35	0.015	3.319	3.379
Clear,Mid	ABC	3.35	0.015	3.318	3.379
Clear,All	ABC	3.34	0.016	3.311	3.375
Blurred,Far	ABC	3.34	0.016	3.310	3.374
Blurred,All	ABC	3.34	0.016	3.307	3.371
Clear,Near	ABC	3.33	0.015	3.302	3.362
Blurred,Target	BC	3.33	0.016	3.294	3.358
Blurred,Near	C	3.32	0.015	3.289	3.349
Clear,Target	D	3.23	0.016	3.200	3.264

Note. Levels not connected by same letter are significantly different ($\alpha = 0.05$, $Q = 3.07$).

As presented in Table 18 and shown in Figure 16, and replicating both Experiment 1 and Experiment 2's set size of four, the all-blurred and all-clear conditions are not significantly different. This further supports a lack of legibility effects and a lack of attentional guidance with undifferentiated stimuli, suggesting random search. Thus, the all-blurred and all-clear conditions again serve as the baseline for the singleton conditions that may influence selective attention. By comparing both Figure 2 and Figure 16, we see the strongest evidence yet in support of the Blur Ignored hypothesis and the strongest rejection of the Blur Repels and Blur Captures hypotheses. Most importantly, the blurred target singleton and all-blurred conditions did not significantly differ from any of the other blur conditions, providing evidence that blur did not influence selective attention. However, the blurred near distractor was significantly faster than the blurred mid distractor. It is unclear why this occurred other than perhaps some capture to the distractors adjacent to the blurred singleton. This would result in the blurred near distractor capturing selective attention toward a distractor and the target. Having one of the adjacent items being the target may have resulted in the faster RT, but this was not predicted by any of the hypotheses. The clear conditions' results replicated and strengthened the conclusions from the set size of four findings, with the clear target singleton being responded to significantly faster than all other clear conditions, which did not significantly differ amongst themselves, suggesting that unique clarity is capturing selective attention. However, capture to a distractor does not influence the RT as greatly as capture to the target. Most importantly, the blurred target singleton's RT was significantly slower than the clear target singletons, which immediately rejects the Blur Capture hypothesis and because the blurred target singleton had a similar RT with all-blurred this rejects the Blur Repels hypothesis, leaving and supporting the Blur Ignored hypothesis.

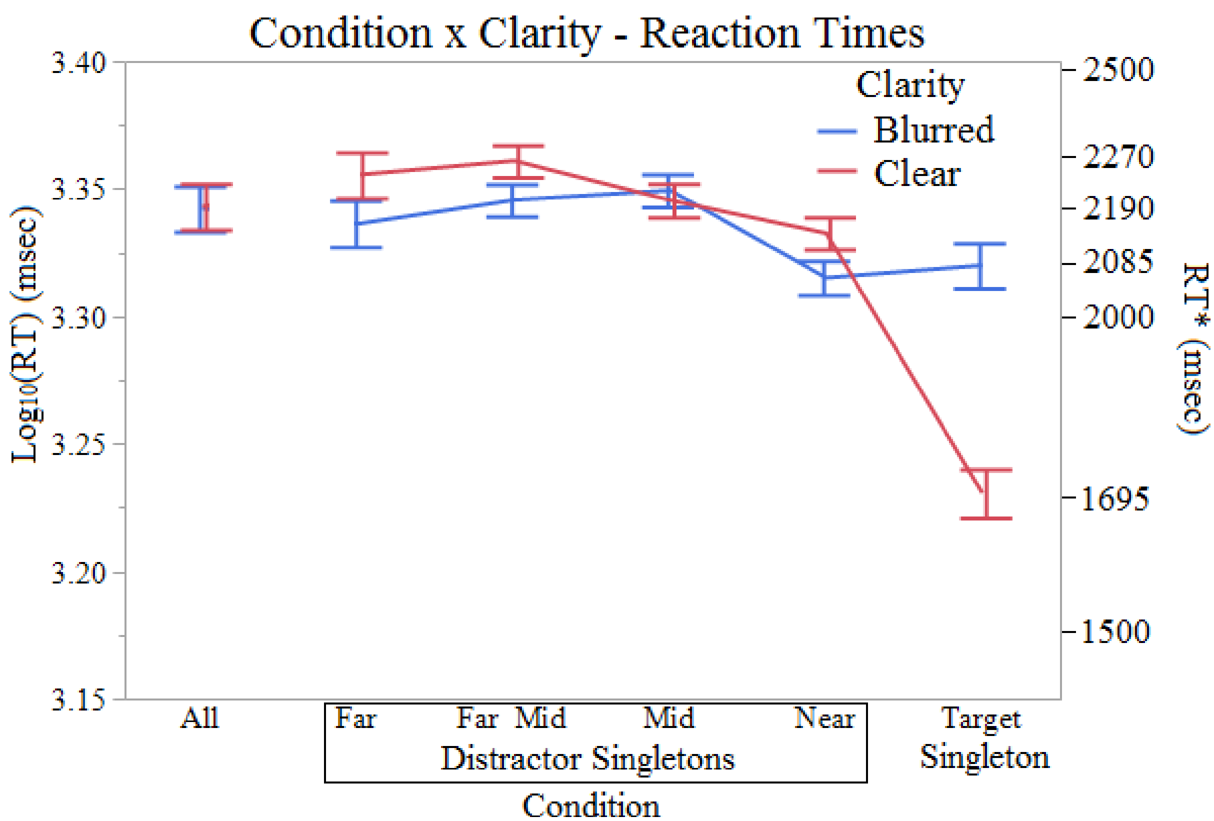

Figure 16. The Log_{10}(RT) *M* for *Condition* x *Clarity* with +/- 1 SEM bars. Secondary y-axis presents RT* values in msec distributed on a logarithmic scale.

Once more, as in Experiment 1 and Experiment 2's set size of four, a model for each predicted hypothesis was used to test which hypothesis explained the data best using linear multilevel modeling and the same equation structure as before. Table 19 displays the parameter estimates for the best model, which was again Hypothesis #3 Blur Ignored. The analyses showed that, in terms of R^2, there is little if any differences between Hypothesis #3 Blur Ignored, with R^2 = .20, adjusted R^2 = .20, RMSE = 0.23, and the other two hypotheses models (Blur Repels and Blur Captures), which each had an R^2 = .19, adjusted R^2 = .19, and RMSE = 0.23. Importantly, however, the BIC values for each model again strongly supported the Blur Ignored model (BIC = -1318.4), which had a value 92 points lower than the Blur Repels model (BIC = -1226.4) and 140.2 points lower than the Blur Captures model (BIC = -1178.2). The likelihood ratios strongly support that Blur Ignored is 9.5×10^{19} and 2.8×10^{30} times more likely to have produced the reaction times than Blur Repels and Blur Captures, respectively. These results are critically important as they provided evidence that unique blur is not influencing the guidance of selective attention.

Table 19

Parameter Estimates Log_{10}(RT) ~ Hypothesis (Blur Ignored) + Log_{10}(Trial) + (Hypothesis (Blur Ignored) + Log_{10}(Trial)|Participant) Model

Fixed Effects	Estimates	Std Error	DFDen	t Ratio	p-value
Intercept	3.493	0.074	58.39	47.04	<.001
Hypothesis 3 - Blur Ignored	0.029	0.004	51.49	6.77	<.001
Log_{10}(Trial)	-0.131	0.032	47.24	-4.07	0.002

Note. DFDen = degrees of freedom used in the denominator.

Discussion

The results of Experiment 2 again found no effects of legibility, and provided even stronger evidence for the Blur Ignored hypothesis, which was largely supported by the comparison from the Tukey's HSD and model fits analyses at both set sizes. Experiment 2's support of the Blur Ignored hypothesis replicated, strengthened, and greatly clarified the results of Experiment 1. The influence the blur/clarity manipulation had on finding the target was greatly amplified compared to Experiment 1, by making the task more difficult having two set sizes (4 & 8), by making the L distractors appear more T-like, and increasing the number of analyzed trials by having a target orientation identification task, instead of target present versus absent task. Across both set sizes, the blur conditions all had similar RTs that did not statistically differ from one another, except for near and mid distractor conditions with the set size of eight. The clear target singleton was responded to much quicker such that it was faster than all other clear conditions, which did not significantly differ amongst themselves, and from all the blurred conditions, as predicted by Blur Ignored. Blur Captures is the easiest competing hypothesis to reject simply because the clear target singleton was responded to faster than the blurred target singleton. Blur Repels is also rejected because the blurred target singleton did not significantly differ from the all-blurred condition. Therefore, unique blur appears not to have guided selective attention, but unique clarity very strongly did.

Chapter 6 - General Discussion

The current study provided evidence that unique blur is ignored by selective attention. In order to draw this conclusion, both experiments were preceded by control studies, which accounted for legibility issues such that differences in RTs were not caused by one level of clarity (Blurred vs. Clear) being harder to identify than the other. Experiments 1 and 2 used rotated L versus T visual search tasks while manipulating blur and clarity in a way that was non-predictive for finding the target. This allowed us to measure RTs to provide evidence of how clarity and blur may guide selective attention. Specifically, faster RTs to the non-predictively blurred or clear targets would indicate the capture of attention by blur or clarity, while slower RTs to the non-predictively blurred targets would suggest that blur repels selective attention, and a lack of change in RTs due to blur or clarity would suggest no influence on selective attention (i.e., ignored). The results of both experiments most strongly supported the hypothesis that clarity captures attention, but blur is ignored.

Results from both experiments suggest that blur is ignored by selective attention based on the comparison of three quantitative prediction models through linear multilevel modeling, which generated BIC values and likelihood ratios to compare the models, and a priori planned comparisons of the *Clarity* x *Condition* interaction. The Blur Ignored prediction model explained the data better than the Blur Captures and Blur Repels prediction models. The general findings were that while unique clarity captures attention, blur neither captures, nor repels, thus is ignored by selective attention resulting in similar search times to conditions without guidance.

The Blur Captures hypothesis was weakly supported in Experiment 1 because the clear and blurred target singletons did not significantly differ from one another. However, in Experiment 2, which amplified the attentional effect by increasing task difficulty and manipulating set size, there were large and meaningful differences between the clear and blurred singleton targets, thus rejecting the Blur Captures hypothesis. Furthermore, the Experiment 2 results showed the blurred target singleton condition had similar RTs to the all-clear and all-blurred conditions whereas the clear target singleton's RT was significantly faster than all three of those conditions. This strongly suggests that the unique clarity is capturing selective attention while unique blur does not, which clearly rejects the Blur Captures hypothesis. This asymmetry in the results for unique blur versus clear items is in contrast to findings for the effects of color singleton pop out, in which, for example, a red square amongst green squares will pop out in a similar manner to a green square amongst red squares. In Experiments 1 and 2 the clear and blurred letters were manipulated such that they were non-predictive of the target's location. Interestingly, Theeuwes (1991) used a non-predictive approach with unique onset and offsets which found capture by both. However, Boot (2005) showed that onsets, but not offsets will capture covert attention when completely unpredictive (i.e., anti-predictive) of target location. The results from Experiment 2 are similar to the findings of Boot (2005), but used the non-predictive approach similar to Theeuwes (1991). Thus it seems that, by analogy to the onset/offset results of Theeuwes, blur and clarity when unique should have captured selective attention, though this was very clearly not the case as only unique clarity captured selective attention. Instead, the current findings are similar to Yantis and Egeth's (1999), where they found that size and luminance singletons captured attention even when non-predictive of the target's location. Both size and luminance varied on prothetic feature dimensions, suggesting that the blur/clear manipulation may also be varying on a prothetic dimension, which is biased toward the capture of selective attention to unique high spatial frequencies (clear) items and not unique low spatial frequencies (blur) when this information is non-predictive of target location. However, this is only speculative, since determining whether spatial frequency information varies on a prothetic or metathetic dimension was not the purpose of the study .

Previous eye tracking research has found when there is a uniquely clear region of an image, eye movements tend to be attracted to that location over other regions that are blurred (Enns & MacDonald, 2012; Khan, Dinet, & Konik, 2011; Loschky & McConkie, 2002; Smith & Tadmore, 2012). If unique clarity is capturing selective attention, then there must be blur surrounding the clarity to create the contrast. This raises the question, then, of whether the capture by unique clarity is actually a result of blur repelling selective attention to the uniquely clear item, or of the uniquely clear item independently capturing selective attention, or both. Enns and MacDonald (2012, Exp. 3) found evidence to support the claim that blur was not repelling attention. The current study extends those findings with Experiment 2, in which the clear target singletons' RTs were faster than the all-clear condition, with the only change between those two conditions being the addition of blur to the distractors in the clear target singleton condition. If those results were due to blur repelling attention, then one would expect that the blurred target singleton condition should have had the largest RTs since as the only blurred item, it would be attended to last. Thus, if unique blur was repelling attention, it should have produced a longer RT of a similar magnitude to the shorter RT for the clear target singletons, as shown in Figure 2, "Blur Repels." However, no such results were found in either Experiments 1 or 2, allowing us to reject the Blur Repels hypothesis.

By rejecting the Blur Captures and Blur Repels hypotheses, our only remaining hypothesis is Blur Ignored. Evidence in favor of this hypothesis combined 1) a null effect for unique blur compared to the all-blurred condition, combined with 2) a positive effect for unique clarity compared to the all-clear condition. Additional support came from comparisons of the BIC values and likelihood ratios for the three quantitative prediction models, in which the Blur Ignored models had the lowest BIC values and high likelihoods of producing the observed reaction times, which strongly supported rejecting the alternative models (Blur Captures & Blur Repels).

Importantly, there is other evidence in the literature that blur can take on an active role in guiding attention. In Enns and MacDonald's (2012) Experiment 4, they manipulated viewers' goal-orientation by having participants search for a unique deviation in image quality such that blur became task-relevant, with the result that unique blur was detected faster than uniquely clear regions. This finding is showing that blur can be used to guide selective attention, if goal-orientation is aligned with blur by being made task-relevant. This suggests that while blur typically serves a passive role in selective attention guidance, it can be used to guide attention if top-down goal-orientation processes switch its role from passive to active. Future research using a similar experimental design to that of Experiment 2 but manipulating goal-orientation of task-relevancy may be able to further provide evidence of blur's function in guiding attention.

Another logical future step to this line of research would be to include eye tracking with a similar design to Experiment 2. Eyetracking would allow earlier measures of how the blur/clarity manipulations guide selective attention, such as the latency to first fixate a uniquely blurred or clear target or distractor as compared to the same targets and distractors in the all-blurred and all-clear conditions. By extending the research from covert to overt attention, the eye movement results could then be used to explain the RT results in finer detail.

The results from the current study are most in line with the findings from Enns and MacDonald's (2012) Experiment 3, in which they found that uniquely clear regions of an image captured attention, but uniquely blurred regions did not, with the uniquely blurred regions not differing from a uniformly blurred image. Similarly, in the current study, the blurred singleton conditions did not differ from the all-blurred conditions. However, the current study goes beyond the Enns and MacDonald (2012) study in a number of important ways. First, the current study used a standard rotated L versus T visual search task, which is well-known to strongly invoke serial search (Wolfe et al., 1989; Egeth & Dagenbach, 1991; Jiang & Chun, 2001; Enns & MacDonald, 2012). Because of this, it was possible to quantitatively model the hypotheses in terms of a serial self-terminating search process influenced by non-informative feature-based capture, here by blur versus clarity. The quantitative models for the alternative competing hypotheses could then be tested using multilevel modeling and a priori planned comparisons. Second, the blur/clarity manipulation was carefully counterbalanced to occur equally often at all peripheral locations, making it non-predictive of target location. Importantly, the current study also controlled for legibility issues, which would otherwise leave open the question of whether the results were due to attentional guidance versus difficulties in blurred letter identification. Finally, the current study brought the effects of blur/clarity on attentional selection into the standard visual search literature, which is the gold standard for talking about attentional guidance, with a paradigm that can be used in further studies.

There are some limitations to both experiments. Experiment 1 had L and T letters which differed in the length of their horizontal and vertical lines, which may explain why the Ls were slightly easier and faster to identify than the Ts in the Pilot Experiment 1 results. This was addressed in Experiment 2 by using the T-like L distractors, which were composed of equal length line segments, and also produced a more difficult serial search, as desired. However, while the task was certainly a serial search there was additional error variance added into the RTs due to the difficulty of making the decision between target or distractor items. This is not ideal as it produces more variability than needed when deciding if the target was pointed to the left or right. It may have been better to use a typical L, instead of the T-like L as the distractor for Experiment 2, as this may have resulted in cleaner RT differences related to the blur/clarity manipulation.

The results from Experiments 1 and 2 provide insight to the role that blur/clarity contrast plays in guiding visual attention, which can have numerous applications. Blur/clarity contrast has already been used by filmmakers for some time to direct viewers' attention in film by varying the depth of field of the camera, focusing on a key region of interest, and thereby blurring the rest of the scene, as shown earlier in Video 1. However, blur/clarity contrast can be used more generally in computer displays to help direct the user's attention to critical information. For example, should a marketing team place an ad online they may want to quickly blur the screen leaving only the ad in focus for a very brief time, then present the screen entirely clear. This quick blur should direct the viewer to the ad on the screen. In a more serious case, a computer can notify its user that a harmful or critical event is going to occur by guiding the user's attention in a similar fashion as the marketing ad to a region on the screen to help resolve the issue. This understanding of blur/clarity contrast and attention could also be applied to machine vision by including blur/clarity contrast in visual saliency models (Itti & Koch, 2001; Vincent, Troscianko, & Gilchrist, 2007), making them even more similar to our own visual system. This could be done by including the asymmetric bias toward uniquely clear regions in saliency algorithms that predict where the most salient item/region is located. Given that blur/clarity contrast is measured in terms of spatial frequency content, such algorithms would need to calculate where there are differences in the range of available spatial frequencies, and pick the area that is most locally unique in terms of having higher spatial frequencies.

Conclusion

Both Experiments 1 and 2 investigated the role that blur/clarity contrast plays in guiding visual selective attention. The experiments used rotated L and T visual search tasks in which blur and clarity were manipulated but non-predictive of the target location. Importantly, the effects of blur/clarity contrast on selective attention could be measured through reaction times, because each experiment was preceded by a pilot study to control for legibility. The results indicated that unique clarity captures attention, while unique blur is ignored. The current study's findings confirm and extend those of Enns and MacDonald (2012), but in a much more fine-grained, robust, and controlled manner, while testing three alternative competing hypotheses (Blur Captures, Blur Repels, and Blur Ignored). The results are, in fact, counter-intuitive, but clear and robustly supported. Future research will use similar methods, but measure eye movements to investigate blur/clarity contrast's influence on guiding selective overt attention, and also investigate how blur's influence on attention may become active when goal-orientation makes it task-relevant.

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Appendix A - Search Sets

When calculating the average number of items searched for each predicted hypotheses' conditions there are four separate sets of probabilities that need to be calculated: Random, Capture, Repel Target, and Repel Distractor searches. Random search set occurs when there is no guidance such as with the all-blurred and all-clear conditions as well as the blurred singletons for the Blur Ignored hypothesis. Capture search set occurs when there is a unique singleton that captures attention for the first item looked at such as any clear singleton condition as well as blurred singletons for the Blur Captures hypothesis. The Repel Target search set only occurs for the blurred target singleton condition for the Blur Repels hypothesis. The Repel Distractor search set only occurs for blurred distractor singleton conditions for the Blur Repels hypothesis.

Experiment 1: Set Size 5

To calculate the average items searched (AIS) for a condition without guidance (random search) the following equation can be used: AIS = P(IS1) + P(IS2) + P(IS3) + P(IS4) + P(IS5), where (P) is probability and (IS) is item searched. To calculate the probability of an IS, first you have to take into account the chance that the item will need to be searched. P(I1) for any experiment and set size is simply 1 because there must be a first item searched in order to find the target. The probability of needing to search a second item is based on the probability that the first item searched was not the target, but a distractor (D), therefore P(IS2) = P(IS2 | IS1D). Table 20 displays the equations for each items probability equation, with the values filled in, and probabilities calculated.

Experiment 1: Set Size 5

Table 20

Random Search Set

Item	Probability of each item being searched	Probability with Set Size 5	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). Easiest way to read IS1D would be to say item searched 1 was a distractor, which means the first item searched was a distractor.

Once the probability for each item being searched in a set size has been calculated, then the AIS can be calculated, where AIS = P(IS1) + P(IS2) + P(IS3) + P(IS4) + P(IS5) = 1 + 0.8 + 0.6 + 0.4 + 0.2 = 3. Therefore, with a set size of five, when there is no guidance (random search) the average number of items searched will be three items such as with the all blur and all-clear conditions across all three predicted hypotheses as well as with the blurred singleton conditions for the Blur Ignored hypothesis. This changes when there is guidance such as when there is a unique item that captures attention.

Table 21

Capture Search Set

Item	Probability of each item being searched	Probability with Set Size 5	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 * 3/4)	0.75
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 1 * 3/4 * 2/3)	0.5
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 1 * 3/4 * 2/3 * 1/2)	0.25

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D). Easiest way to read IS1D would be to say item searched 1 was a distractor, which really means the first item search was a distractor.

The Capture search set allows for two types of conditions' AIS to be calculated. The first is the target singletons when they capture attention this will always result in the first item searched resulting in finding the target (Assumption 2). The second condition group is the distractor singletons when they capture attention. The first item capturing attention is not the target, therefore the first and second items must be searched as can be seen above in Table 21 by having both P(IS1) and P(IS2)'s probability equal to one. Since the first item was not the target the remaining items are either all-clear or all-blurred and a random search will then proceed until the target is found.

The Repel Target search set is only needed for the blurred target singleton condition for the Blur Repels hypothesis. Table 22 displays the Repel Target search set equations and probabilities. The probability of looking at all five items is one because the target is the unique item that is blurred and when blur repels attention, then it should be the last item searched (Assumption 3).

Table 22

Repel Target Search Set

Item	Probability of each item being searched	Probability with Set Size 5	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

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D). Easiest way to read IS1D would be to say item searched 1 was a distractor, which really means the first item search was a distractor.

The Repel Distractor search set is only needed for the blurred distractor singleton condition for the Blur Repels hypothesis. Table 23 displays the Repel Distractor search set equations and probabilities. The probability of looking at each item is based on a smaller set size (SS – 1) because the blurred item is a distractor and based on Assumption 3 this item should be the last item looked at. Therefore, a random search will take place based on the unique item being removed because the target will be found before needing to look at the blurred distractor singleton.

Table 23

Repel Distractor Search Set

Item	Probability of each item being searched	Probability with Set Size 5	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 3/4)	0.75
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 3/4 * 2/3)	0.5
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 3/4 * 2/3 * 1/2)	0.25

Note. Terms in the table are Probability (P), Item Searched (IS), and Distractor (D). Easiest way to read IS1D would be to say item searched 1 was a distractor, which really means the first item search was a distractor.

Through these probability search sets all of the conditions for each predicted hypothesis can be calculated based on a set size of five. Experiment 2 also uses the same four probability search sets, but they vary in the number of items that can be searched. The following are the four probability tables for each of the set sizes for Experiment 2.

Experiment 2: Set Size 4

Table 24

Random Search Set

Item	Probability of each item being searched	Probability with Set Size 4	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 3/4)	0.75
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 3/4 * 2/3)	0.5
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 3/4 * 2/3 * 1/2)	0.25

Table 25

Capture Search Set

Item	Probability of each item being searched	Probability with Set Size 4	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 * 2/3)	0.67
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 1 * 2/3 * 1/2)	0.33

Table 26

Repel Target Search Set

Item	Probability of each item being searched	Probability with Set Size 4	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

Table 27

Repel Distractor Search Set

Item	Probability of each item being searched	Probability with Set Size 4	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 2/3)	0.67
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 2/3 * 1/2)	0.33

Experiment 2: Set Size 8

Table 28

Random Search Set

Item	Probability of each item being searched	Probability with Set Size 8	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 7/8)	0.875
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 7/8 * 6/7)	0.75
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 7/8 * 6/7 * 5/6)	0.625
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 7/8 * 6/7 * 5/6 * 4/5)	0.5
6	P(IS6) = P(IS6 | IS1D * IS2D * IS3D * IS4D * IS5D)	P(IS6) = P(1 | 7/8 * 6/7 * 5/6 * 4/5 * 3/4)	0.375
7	P(IS7) = P(IS7 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D)	P(IS7) = P(1 | 7/8 * 6/7 * 5/6 * 4/5 * 3/4 * 2/3)	0.25
8	P(IS8) = P(IS8 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D * IS7D)	P(IS8) = P(1 | 7/8 * 6/7 * 5/6 * 4/5 * 3/4 * 2/3 * 1/2)	0.125

Table 29

Capture Search Set

Item	Probability of each item being searched	Probability with Set Size 8	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 * 6/7)	0.857
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 1 * 6/7 * 5/6)	0.714
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 1 * 6/7 * 5/6 * 4/5)	0.571
6	P(IS6) = P(IS6 | IS1D * IS2D * IS3D * IS4D * IS5D)	P(IS6) = P(1 | 1 * 6/7 * 5/6 * 4/5 * 3/4)	0.429
7	P(IS7) = P(IS7 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D)	P(IS7) = P(1 | 1 * 6/7 * 5/6 * 4/5 * 3/4 * 2/3)	0.286
8	P(IS8) = P(IS8 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D * IS7D)	P(IS8) = P(1 | 1 * 6/7 * 5/6 * 4/5 * 3/4 * 2/3 * 1/2)	0.143

Table 30

Repel Target Search Set

Item	Probability of each item being searched	Probability with Set Size 8	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
7	P(IS7) = P(IS7 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D)	P(IS7) = P(1 | 1 * 1 * 1 * 1 * 1 * 1)	1
8	P(IS8) = P(IS8 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D * IS7D)	P(IS8) = P(1 | 1 * 1 * 1 * 1 * 1 * 1 * 1)	1

Table 31

Repel Distractor Search Set

Item	Probability of each item being searched	Probability with Set Size 8	Probability
1	P(IS1) = 1	P(IS1) = 1	1
2	P(IS2) = P(IS2 | IS1D)	P(IS2) = P(1 | 6/7)	0.857
3	P(IS3) = P(IS3 | IS1D * IS2D)	P(IS3) = P(1 | 6/7 * 5/6)	0.714
4	P(IS4) = P(IS4 | IS1D * IS2D * IS3D)	P(IS4) = P(1 | 6/7 * 5/6 * 4/5)	0.571
5	P(IS5) = P(IS5 | IS1D * IS2D * IS3D * IS4D)	P(IS5) = P(1 | 6/7 * 5/6 * 4/5 * 3/4)	0.429
6	P(IS6) = P(IS6 | IS1D * IS2D * IS3D * IS4D * IS5D)	P(IS6) = P(1 | 6/7 * 5/6 * 4/5 * 3/4 * 2/3)	0.286
7	P(IS7) = P(IS7 | IS1D * IS2D * IS3D * IS4D * IS5D * IS6D)	P(IS7) = P(1 | 6/7 * 5/6 * 4/5 * 3/4 * 2/3 * 1/2)	0.143

Appendix B - Pilot Experiment 1 Counterbalancing Error

Experiment 1 Pilot study's counterbalancing error for position of letter location (See Table 32). This error was systematic across all participants with the same distribution of trials for each position. While the number of trials for each position is off, the counterbalancing between letter and clarity is still correct.

Table 32

Counterbalancing Error for Position of Letter Location

		Position				
Letter	Clarity	1	2	3	4	5
L	Clear	23	20	18	19	20
L	Blur	20	14	22	24	20
T	Clear	20	21	23	19	17
T	Blur	17	25	17	18	23

Appendix C - Pilot Experiment 1 Random Effect Structures for Accuracy

Table 33

Comparisons of Random Effect Structures for Accuracy in Pilot Experiment 1

Random Effects Structure	BIC
1 | Participant	4495.8*
Letter | Participant	4510.4
Clarity | Participant	4514.7
Letter + Clarity | Participant	4538.8
Letter + Clarity + Letter x Clarity | Participant	4577.1
Letter + Clarity + Log(Trial) | Participant	4568.7***
Letter + Clarity + Letter x Clarity + Log(Trial) | Participant	4616.2***

Note. * Indicates the random effect structure selected for the final model. *** Indicates a failure to converge.

Appendix D - Pilot Experiment 2 Random Effect Structures for Accuracy

Table 34

Comparisons of Random Effect Structures for Accuracy in Pilot Experiment 2

Random Effects Structure	BIC
1 | Participant	3370.5*
Letter | Participant	3377.6
Clarity | Participant	3401.6
Letter + Clarity | Participant	3432.9
Letter + Clarity + Letter x Clarity | Participant	3432.9***
Letter + Clarity + Log(Trial) | Participant	3384.5
Letter + Clarity + Letter x Clarity + Log(Trial) | Participant	3422.2***

Note. * Indicates the random effect structure selected for the final model. *** Indicates a failure to converge.

Appendix E - Accuracy Card

Name:______________________________

Break 1 Accuracy Score: ______________

Break 2 Accuracy Score: ______________

Break 3 Accuracy Score: ______________

Overall Accuracy Score: ______________

Figure 17. Accuracy Card.