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Effects of Signal Ambiguity and Signal Location on Target Detection Under Varying Degrees of Time Constraint

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EFFECTS OF SIGNAL AMBIGUITY AND SIGNAL LOCATION ON TARGET DETECTION UNDER VARYING DEGREES OF TIME CONSTRAINT

by

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ABSTRACT

EFFECTS OF SIGNAL AMBIGUITY AND SIGNAL LOCATION ON TARGET DETECTION UNDER VARYING DEGREES OF TIME CONSTRAINT

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The purpose of the current study was to investigate the effects of decision-making strategies and tendencies, time constraint, and signal characteristics on decision-making performance utilizing the fuzzy signal detection theory framework. Participants were tasked with deciding whether x-ray images of passenger luggage contained hazardous objects.

The first objective of the study was to develop a methodology for quantifying optimizing versus satisficing tendencies in decision making through direct measurement and observation.

The second objective of the study was to examine how time constraint and specific signal characteristics contribute to decision making. Interestingly, despite having more time available to conduct a comprehensive search, participants in the global time constraint condition who were able to self-terminate information search tended toward satisficing. They also had shorter overall search durations and greater sensitivities than participants in the local time constraint condition, and had shorter search durations for central compared to eccentric targets. Across time constraint conditions and decision tendencies, participants had greater sensitivities for centrally located targets compared to eccentrically located targets and for ambiguous signals with moderate to high degrees of target category membership ($.40 \leq s \leq .80$). Within each time constraint condition, there

were differences in response criteria as a function of signal ambiguity. Participants in the local condition had more liberal response criteria compared to participants in the global condition.

There was no significant effect of self-terminated search duration on sensitivity or response criteria. To examine the effect of participant control over search duration, participants in the global time constraint condition with average search durations of 3500-4500 ms were selected for comparison to participants in the local 4000 ms fixed-interval time constraint condition. There were significant differences in sensitivities such that participants in the global time constraint condition with ~4000 ms search durations had significantly higher sensitivities, indicating an effect of participant control over search duration. There were no significant differences in response criteria.

The current study investigated decision making elements that contribute to efficient and effective operator performance of information search and target detection. In addition to operator characteristics that impact performance outcomes, characteristics of the signal itself may also moderate signal detection.

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CHAPTER 1

INTRODUCTION AND BACKGROUND OF THE STUDY

National security, luggage screening, and visual search

Without question, terrorist attacks and threats over the past decade have amplified the attention paid to transportation, and specifically aviation, security. The Transportation Security Administration (TSA) was established by the Aviation and Transportation Security Act and charged with the responsibility of securing the civil aviation system by means that include screening all passengers and their luggage items traveling via commercial passenger aircraft (GAO, 2011). The Government Accountability Office (GAO, 2007) noted that there are several elements involved in the airline passenger and carryon luggage screening process. Transportation security officers (TSOs) screen all passengers and their carryon luggage prior to allowing passengers access to their departure gates. Among other responsibilities, TSOs attempt to detect prohibited items that passengers attempt to transport beyond security checkpoints. TSOs employ technology including walk through metal detectors, X-ray machines, handheld metal detectors, and explosive trace detection (ETD) equipment to aid detection. Standard operating procedures establish the process and standards by which TSOs are to screen passengers and their carryon items at screening checkpoints (GAO, 2007). By such means, TSA intends to minimize the passage of potentially hazardous items through security checkpoints.

Operators in a decision making task involving visual search or screening must utilize cognitive and perceptual resources to interpret the display outputs of a device or visual scene. Therefore, visual search performance errors and errors of decision making

are possible. Degraded visual search behaviors or decision processes may preclude detection of threat objects present in a luggage item.

Repeated audits conducted by the Federal Aviation Administration (FAA) reveal consistently high miss rates by TSOs conducting luggage screening. The miss rate for potentially dangerous items at security checkpoints was approximately 13% in 1978. By the late 1980's, the miss rate had risen to 20%, and further performance declines were noted as testing continued through the late 1990s. Post-1990s data continue to demonstrate a negative trend in detection performance, but specific figures are no longer publicly reported. The Government Accountability Office (GAO, 2005) noted that threat detection performance of luggage screeners continues to be a concern and a need to understand performance deficits and improve them exists.

Perceptual, cognitive and decision making challenges in luggage screening

One of the primary challenges in luggage screening is that the full member set of potentially dangerous targets in weapon categories is unknown (Evans, 2005). Target categories may include guns, knives, and explosives, but the individual targets within these categories may take many forms, and may even be unique and novel configurations. This is particularly true for explosive devices and disassembled or camouflaged firearms. Ever-changing item compositions or presentations add to the difficulty of accurately and efficiently identifying objects in the search field. Furthermore, an object may be perceived as having some of the qualities or characteristics of a target without being a complete match. That is, the degree of target category membership may vary, compounding the difficulty of identification.

In addition to the variability of target presentation, the position of a target within the display can also add difficulty to the visual search task. Monk (1981) found longer search durations for targets appearing in the outer half of a display than in the inner half, terming this phenomenon the "edge" or "eccentricity" effect. Wolfe, O'Neil, and Bennet (1998) examined miss rate and detection time for targets situated at different locations on a visual display and found a moderate increase in errors for targets in eccentric portions of the display. This finding implies that eccentricity effects are not due to purely visual processes without an attentional component (Wolfe, O'Neil, & Bennet, 1998). Essentially, individuals prefer to allocate attention to centrally located portions of a display and neglect eccentrically located portions. The authors assert that eccentricity effects are not fully accounted for by a peripheral reduction in visual sensitivity, and attention is responsible for the allocation of stimuli inspection time and resources.

Previous research has examined eccentricity effects in a variety of visual search tasks. Schroeder, Stern, Stoliarov, and Thackray (1994) examined Air Traffic Control (ATC) scanning and monitoring behaviors across a range of variables including time on task and target location across four blocks on each of three days. The authors found performance decrements due to time on task for the complex monitoring tasks associated with detection and decision making, in line with previous research (Thackray & Touchstone, 1991). Additionally, detection times for targets in the outer 50% of the display were significantly longer than detection times for targets in the inner 50% of the display. The data also revealed a trend toward more missed outer targets (8, 7, and 7 across the three days) than inner targets (4, 0, and 1 respectively). Schroeder, Stern, Stoliarov, and Thackray (1994) also noted that whereas detection performance for inner

targets improved over the course of the three days, detection performance for outer targets remained relatively unchanged, indicating that participants tended to neglect the periphery of the display.

Thackray (1990) also examined the effects of location on target detection in a study of signal conspicuity in a radar monitoring task. In that study, half of the signals were presented at outer locations of the display and half at inner locations. Thackray found a significant main effect for target location on response time, whereby participants took longer to identify eccentric targets than central targets. The authors note that eccentricity effects have been reported by in various paradigms including visual search (Baker, Morris, & Steedman, 1960; Enoch, 1959) and radar monitoring tasks (Baker, 1958). It is important to assess factors that contribute to the neglect of eccentric regions of a display; as such, inattention can lead to higher miss rates, and may generate predictable vulnerabilities in airline security. Individuals with malicious intent may capitalize on increased security vulnerability by placing potentially hazardous items in the outer portions of luggage items. Examining whether decision making tendencies contribute to eccentricity effects may allow for mitigation of such degraded performance if trends emerge.

In the luggage screening paradigm, the screener is tasked with detecting potential threats in the form of a variety of targets. Because the entire range of possible weapon categories is unknown and target presentation locations vary, this type of signal detection task is particularly challenging and may lead to increased uncertainty on the part of the screener during the decision making process. The luggage screener typically sets a lower threshold for the minimum amount of evidence required to endorse signal presence in a

display (Green & Swets, 1988).The setting of this threshold and the success of the screener's search strategies can be affected by a variety of factors as discussed in the section above.

Whether an individual is screening passenger luggage for weapons, scanning assembly line production for a malformed product, or monitoring a radar screen for enemy intrusions, the detection of a critical signal is of prime importance. The value of a hit or the cost of a miss is dependent upon the task at hand. Regardless of the cost of missing a target, it is imperative to have a means of assessing operator performance. The method chosen can impact understanding of operator characteristics in occupational tasks that involve reacting to signals. Hancock (2005) notes that a situation analysis utilizing binary fail or no-fail demarcations of outcomes disregards many behavioral aspects that inform potential outcomes, though many assessments continue the tradition of utilizing crisp signal detection theory analysis to calculate performance indices. A comprehensive assessment technique that accounts for behavioral tendencies in decision making, as opposed to just discrete misses, can provide a more appropriate performance assessment for an operator when determining current operator functioning and predicting future task execution.

Signal detection theory

Performance in a decision making task can be assessed by means of a Signal Detection Theory (SDT) analysis. SDT was originally developed to address a practical problem. Engineers designing communication networks utilized this type of analysis as a means of assessing receipt of noisy radio signals (Peterson, Birdsall, & Fox, 1954), and modified and extended it to describe human performance of signal detection (Tanner &

Swets, 1954). This allowed researchers to address the problem of signal detection rate confounding the observer's perceptual ability from the operator's response criteria biases. Because SDT treats sensitivity as a continuous variable, the use of SDT precludes the problems associated with previous absolute and difference thresholds approaches , such as the method of limits or the method of constant stimuli, that viewed perceptual sensitivity as a discrete state (MacMillan & Creelman, 2005). SDT has been applied in a wide range of domains, including aviation, weather prediction, medical applications, military command and control, air traffic control, security, and personnel decisions (Bisseret, 1981; Swets & Pickett, 1982). Stanislaw and Todorov (1999) suggest that SDT is applicable in any situation in which an operator must engage in decision making under some degree of uncertainty.

There are several primary assumptions that must be met to apply SDT to a research paradigm or *in situ* assessment (Wickens, 2002; Stanislaw & Todorov, 1999). Signals, both as present in the environment and as received and represented in the brain during sensation and perception, are essentially always surrounded by noise or random variation. Noise may be comprised of variation in the environment or any properties of the stimulus itself that reduce salience. Continual neural activity in the sensory and perceptual systems also generates noise. The noise is normally distributed along the Gaussian equal variance model. The noise distribution is either normal or transformable to a normal distribution. Whereas traditional psychophysical models regard the observer as a sensor, SDT characterizes the observer as both a sensor and a decision maker. These are considered to be discrete processes that are measured using different indices, namely response bias and sensitivity. In the decision making component of a task, the observer

assumes a threshold criteria that determines the minimum amount of sensory and perceptual evidence required to endorse a "signal present" response. Sensitivity and response bias are independent of one another.

SDT is used as an analysis technique for assessing performance when the task is to categorize potentially ambiguous data as a non-signal or a signal plus noise. SDT is applicable when categorization requires a binary decision as to the presence of a signal in the data. The discernibility of a signal is affected by the degree of noise in the system that interferes with optimal performance of the signal detection task. There are two stages of information processing that are involved in detection tasks to which SDT is applicable. First, the operator accrues sensory data regarding the presence or absence of a signal (measured by an index of sensitivity d'). Based on the accumulated evidence, the operator must then make a decision as to whether there is sufficient indication of signal presence (measured by an index of response bias or criterion setting c) (Green & Swets, 1988).

There are four possible response outcomes in SDT. These outcomes can be represented in a Punnet square-type diagram, referred to as a truth table, in which the state of the world is on the horizontal axis, and the operator response is on the vertical axis (see Figure 1; see Figure 2 for truth table with sample values). Each condition has two mutually exclusive categories: signal present and signal absent, and the interaction of the two conditions produces an outcome. A rate can be calculated for each of the four possible response categories. Rates for hits and misses are calculated by dividing the number of signal present and signal absent operator responses, respectively, by the number of signal present trials. Likewise, rates for false alarms and correct rejections can

be calculated by dividing the number of signal present and signal absent operator responses by the number of signal absent trials.

Hit, false alarm, miss, and correct rejection rates, as well as response criteria and sensitivity, are calculated for each operator participant. The standard formulas for crisp SDT are utilized (Wickens, 2002, p. 6):

Hit rate: $$HR = \frac{\textit{Number of signal present responses to signal present trials}}{\textit{Number of signal present trials}}$$

False alarm rate: $$FAR = \frac{\textit{Number of signal present responses to signal absent trials}}{\textit{Number of signal absent trials}}$$

Miss rate: $$MR = 1 - HR = \frac{\textit{Number of signal absent responses to signal present trials}}{\textit{Number of signal present trials}}$$

Correct rejection rate: CRR = 1 –

$$FAR = \frac{\textit{Number of signal absent responses to signal absent trials}}{\textit{Number of signal absent trials}}$$

Sensitivity: $d' = z(HR) - z(FAR)$

Response criterion setting: $c = 2.71828183^{(-0.5*(z(HR) - z(CRR)))}$

		State of the world	
		Signal present	*Signal absent*
Operator Response	*Signal present*	Hit	False Alarm (FA)
	Signal absent	Miss	Correct Rejection (CR)

Figure 1. Crisp signal detection theory truth table

Participant	Trial	Signal (s)	Response (r)	Hit	FA	Miss	CR
1	1	1	1	1	0	0	0
1	2	1	0	0	0	1	0
1	3	0	0	0	0	0	1
1	4	0	1	0	1	0	0
1	5	0	0	0	0	0	1
1	6	1	1	1	0	0	0
1	7	0	0	0	0	0	1
1	8	1	1	1	0	0	0
1	9	0	1	0	1	0	0
1	10	1	0	0	0	1	0

Figure 2. Crisp signal detection truth table with sample values

Swets, Dawes, and Monahan (2000) note that data or signals should be considered in terms of higher values of degree of evidence being associated with the positive diagnostic alternative, and lower values being associated with the negative alternative. The operator adopts decision criteria or response criteria that set the minimum threshold of evidence required to respond that a signal is present. Because of the complexity of signal discrimination tasks, it is nearly inevitable that an operator will err. However, by altering the response criteria, it is possible for human respondents to implement some control over the type of errors that are made. By lowering the response threshold, or setting a more liberal response criteria, the operator requires less confirmatory data to indicate that a signal is present. Raising the response threshold, or setting a more conservative response criteria, increases the amount of data necessary for the operator to respond that a signal is present.

Sensitivity is the ability of an operator to distinguish between signal and noise. Perceptual sensitivity is generally agreed to be independent of the criteria the observer sets (i.e., the response bias). Sensitivity depends on the strength of the signal and noise and the amount of overlap between the two. It is an evaluation of the intensity of the response that is independent of the response criteria (see Figure 3).

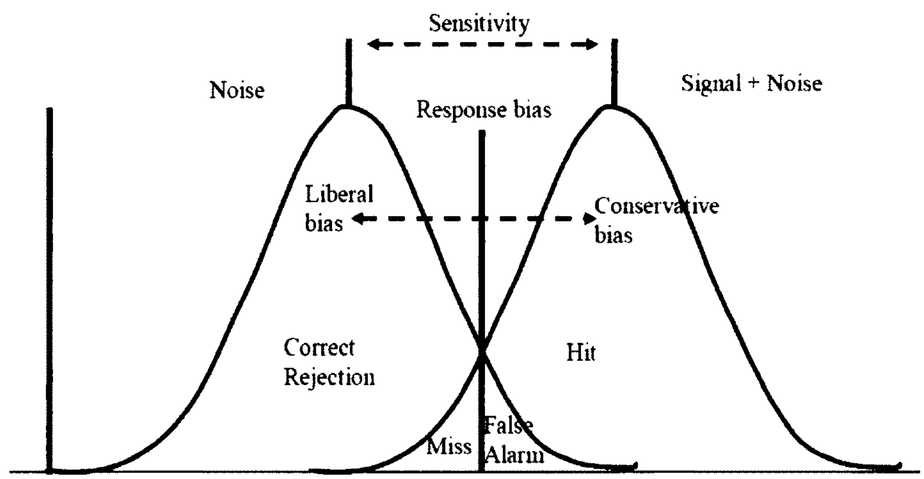

Figure 3. Signal detection theory model

SDT is a useful tool for analyzing two-alternative forced choice decision making in the presence of uncertainty. Dichotomously defined outcomes have practical value in the immediate appraisal of a single, discrete event-moment or observation, such as determining whether there is an interruption of or intrusion upon the current state of affairs. This would include a weapon in a luggage search or an enemy aircraft on a radar display. However, constraining signal and response data into one of two dichotomous

categories can result in the loss of important information about both the signal and the operator's response.

Fuzzy signal detection theory

Fuzzy signal detection theory (FSDT), an extension of traditional or crisp SDT, involves an alternate method of defining both signal and response characteristics to maximize the volume of information available regarding the state of the world and an operator's decision making tendencies. Parasuraman, Masalonis, and Hancock (2000) note that FSDT poses an advantage over traditional SDT by systematically capturing the information present in a continuum, rather than delimiting information capture to the endpoints. An analysis utilizing fuzzy SDT may provide predictive value beyond the information available in a tradition SDT analysis of operator performance by allowing the signal and response to assume a hypothetically infinite range of values between zero and one. Evaluating these values as continuous variables provides the greatest amount of available information about both signal qualities and operator response characteristics.

In the traditional SDT model, the state of the world is restricted to crisp, discrete, mutually exclusive categories. However, dichotomous categories may not accurately represent the true state of the world. It is not uncommon, because of the diversity and nature of signals that are important to operators across a variety of domains, for a signal or an event to have varying degrees of both signal and nonsignal properties or characteristics. Degree of categorical membership can be accounted for by utilizing the FSDT model, which allows a given stimulus or event to belong to more than one category. As category membership is not necessarily mutually exclusive, a signal or event may be classified as both a hit and a false alarm to different degrees depending on the

respective relative degree of category membership in terms of signal-like and nonsignal-like properties. It is possible for uncertainty or dual categorical membership to exist not only in the observer with respect to operator response, but in the signal or event. The setting of response criteria threshold and the general efficacy of the operator's search strategies and procedures can be affected by how the operator perceives the signal itself.

Targets may be present either as discrete, absolute signals, or may be only partially observable or discriminable. The treatment of the "signalness," or degree of signal, of stimuli as a continuous variable is termed fuzzification (Parasuraman, Masalonis, & Hancock, 2000). This is the process by which degree of non-binary categorical membership is assigned. Events can belong to the set "signal" (s) to a degree ranging from 0-1. Events can belong to the set "response" (r) to a degree ranging from 0-1. Mapping functions for s relate the signal value to a variable that depicts the true state of the world. Mapping functions for r may be based, for example, on operator confidence ratings of signal presence, a method used in traditional SDT (Green & Swets, 1988; MacMillan & Creelman, 1991). A mapping function for the response set relates the operator response to a response variable. To assign degrees of (s, r) membership to events, it is necessary to evaluate all possible states of the world and operator responses using mapping functions. Ideal or optimal performance occurs when $r = s$, as the operator response is precisely mapped to the degree of signal actually present. However, it is also possible that signal-response mappings may result in $s > r$ or $s < r$. When $r > s$, some degree of false alarm category membership will ensue, as operator response exceeds the degree of actual signal. On the contrary, when $r < s$, some degree of miss category membership ensues, as operator response is less than the degree of actual signal. Ideal

performance occurs when $r = s$, as the operator response is appropriately mapped to the degree of signal actually present.

Hit, miss, false alarm, and correct rejection category membership is calculated for each trial utilizing the formulas proposed by Parasuraman, Masalonis, and Hancock (2000):

Hit: $H = \min(s, r)$

False Alarm: $FA = \max(r - s, 0)$

Miss: $M = \max(s - r, 0)$

Correct Rejection: $CR = \min(1 - s, 1 - r)$

To calculate hit, miss, false alarm, and correction rejection rates for each participant, the following formulas (Parasuraman, Masalonis, & Hancock, 2000, p. 648) are utilized. The term i denotes the trial number and the term N denotes the total number of trials (see Figure 4 for truth table with sample values).

Hit rate: $HR = \sum(H_i)/ \sum(s_i)$ for $i = 1$ to N

False alarm rate: $FAR = \sum(FA_i)/ \sum(1 - s_i)$ for $i = 1$ to N

Miss rate: $MR = \sum(M_i)/ \sum(s_i)$ for $i = 1$ to N

Correct rejection rate: $CRR = \sum(CR_i)/ \sum(1 - s_i)$ for $i = 1$ to N

Szalma and O'Connell (2011) and Stafford, Szalma, Hancock, and Mouloua (2003) have demonstrated that fuzzy hit and false alarm rates can be used to calculate measures of sensitivity. Stafford, Szalma, Hancock, and Mouloua (2003) assert that response criteria can also be calculated using fuzzy indices.

Sensitivity: $d' = z(HR) - z(FAR)$

Response criteria: $c = 2.71828183^{(-0.5*(z(HR) - z(CRR)))}$

Participant	Trial	Signal (s)	Response (r)	Hit	FA	Miss	CR
1	1	0.6	0.8	0.6	0.2	0.0	0.2
1	2	1.0	0.2	0.2	0.0	0.8	0.0
1	3	0.4	0.2	0.2	0.0	0.2	0.6
1	4	0.6	0.6	0.6	0.0	0.0	0.4
1	5	0.0	0.4	0.0	0.4	0.0	0.6
1	6	1.0	0.8	0.8	0.0	0.2	0.0
1	7	0.2	0.0	0.0	0.0	0.2	0.8
1	8	1.0	1.0	1.0	0.0	0.0	0.0
1	9	0.8	1.0	0.8	0.2	0.0	0.0
1	10	0.0	0.0	0.0	0.0	0.0	1.0

Figure 4. Fuzzy signal detection truth table with sample values

FSDT is applicable to aviation and air traffic control (ATC). Assessments of air traffic safety utilizing traditional SDT assume discrete divisions of states of the world into mutually exclusive, dichotomous categories, namely noise or signal plus noise. However, *in situ*, the signal, such as a runway incursion or a loss of separation, varies over time and by context. Traditional SDT analyses of a situation constitute a signal as either an unequivocal presence ($s = 1$) or an unequivocal absence ($s = 0$). Likewise, the operator response to a scenario is also classified as $r=1$ or $r=0$, which does not account for confidence in or strength of the decision. FSDT, on the other hand, allows for the classification of an event such as an aircraft-to-aircraft conflict as belonging to the signal set with some degree of s between zero and one, and belonging to the response set with some degree of r between zero and one.

Because of its ability to maximize the availability of information, FSDT has been recommended for use in monitoring possible collisions in ATC (Parasuraman, Masalonis,

& Hancock, 2000). According to Federal Aviation Administration (FAA) regulations, two aircraft must maintain a separation of 5 nautical miles (nm) horizontally and 1,000 ft vertically. When either of these critical thresholds is breached, this meets the legal definition of a conflict in the flightpath. Traditional or crisp signal detection theory indicates the presence of a signal specifying an unsafe state at the threshold. FSDT, however, can provide information regarding a potential conflict prior to the official loss of separation as a function of the monotonic curve discussed previously. For example, as the distance between two aircraft (a) approaches or violates separation minima, the value of s increases monotonically. Alternately, in crisp SDT, when a > 5nm, $s = 0$, and when a < 5nm, $s = 1$. While developments in ATC may lead to altered criteria for separation minima in the Next Generation Air Transportation System (NextGEN), FSDT would still be applicable given its ability to forecast and present potential conflicts.

Masalonis and Parasuraman (2003) note that safety or criteria thresholds imposed by management or by artificial means may be arbitrary indicators. The authors note the example of the 5 nm horizontal separation of aircraft required by air traffic control (ATC) regulations in the United States. A separation of 0.1 nm has different safety implications than does a separation of 4.9 nm, though this differential is lost in the information conveyed by a traditional signal present/signal absent examination of a radar display utilizing a 5 nm critical threshold. The masking of proximate potential threats by the division of observations using an arbitrary criteria threshold may be problematic. These artificial dichotomies affect the determination or evaluation of operator performance, as well as current or future situation conditions.

When responding to a critical signal, operators can have varying degrees of confidence in their responses (Masalonis & Parasuraman, 2003). Just as the signal itself may be considered "fuzzy," as explicated in the above examples regarding lateral separation of aircraft or degree of target category membership, the response to a signal, by either a human operator or an automated decision aid, may also be considered "fuzzy." The definition and presentation of a signal *in situ* is generally less dichotomous than in controlled laboratory settings or as delineated in operational guidelines. The operator's response to the question of whether a signal is absent or present can fall on a continuum that accounts for certainty in his or her decision, which may be due to ambiguity in the signal itself or the extent to which he or she considers the signal to have category membership. The response continuum can account for the amount of information perceived by the operator, which in turn may be moderated by behavioral decision making tendencies.

In the current study, operator response value data were plotted by the signal along a continuum of degree of target category membership. It was anticipated that the data would best be modeled using a sigmoid function, as all derivatives would be positive and the system was expected to saturate at higher values of s. Perhaps due to the high cost of a miss in the luggage screening domain, there is a slowing of increasing values of r as saturation is reached when perceived s exceeds some critical threshold. The exemplar model (see Figure 5) is plotted utilizing the sigmoid function $r = 1/[1 + (s/\mathrm{k})^{\mathrm{n}}]$, whereby k is the constant 0.35 and the exponent n equals -4 to achieve the desired sharpness of the mapping function. The data from the current study were expected to follow or

approximate this model and preserve the monotonic increasing function within the restricted domain $0 < s < 1$.

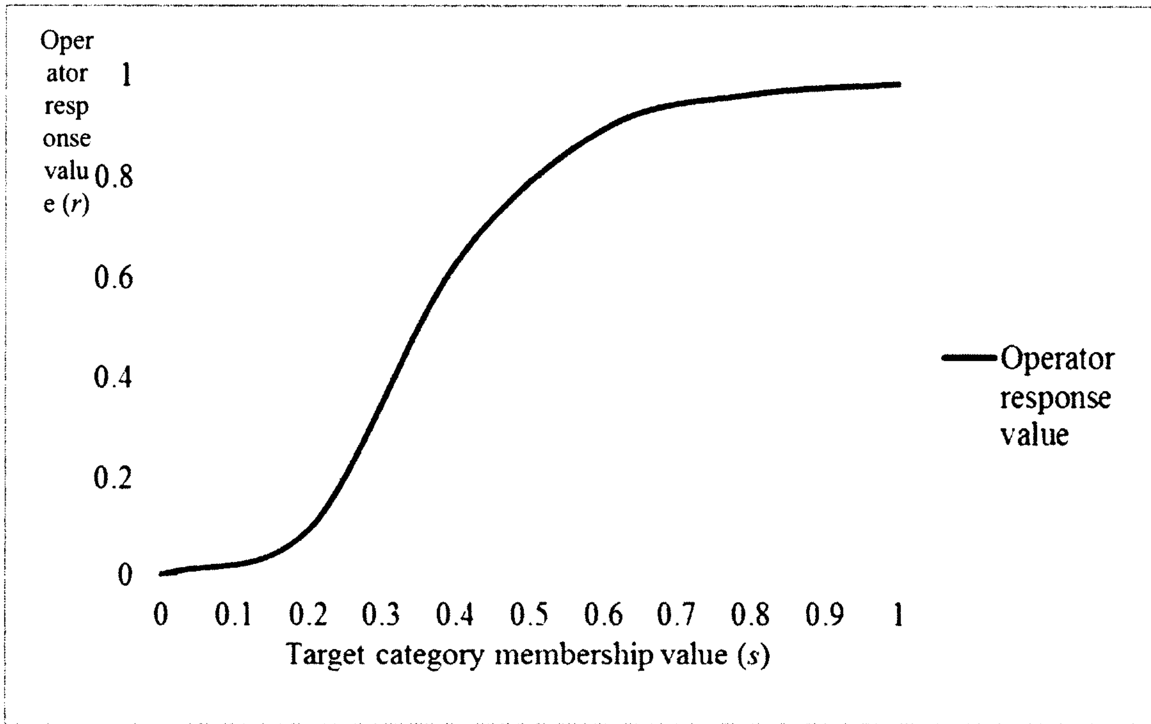

Figure 5. Predicted sigmoid mapping function relating signal value, *s*, to operator response value, *r*

Optimizing versus satisficing

Signals may vary between zero and one in degree of category membership, and operator responses may also range between zero and one, either as mapped to an ambiguous signal or based on confidence in or strength of the decision. In this way, operator responses may reflect characteristics of the signal itself, or may reveal decision making tendencies of the operator. Behavioral decision making is frequently considered

from the perspective of conformity with or deviations from the axioms of rationality and utility maximization (Parker, Bruine de Bruin, & Fischhoff, 2007). From acknowledgement of the merits of these deviations evolved the theory of bounded rationality and examinations of satisficing as a valid strategy for selecting an option that suffices without providing the highest expected utility value. Schwartz et al. (2002) discuss the implausibility of the assumption of complete information, a tenet of rational choice theory, which echoes Gigerenzer and Goldstein's (1996) conceptualization of the human decision maker as having limited time, information, and computational or processing power. Schwartz and colleagues note that when dealing with such cognitive limitations, information can be treated as a commodity that comes at a cost, such as time. Nenkov, Morrin, Ward, Schwartz, and Hulland (2008) assert that the view of information as a commodity may entail maximizers being willing to expend resources in search of an optimal solution, while satisficers weight the disutility of the expenditure of time and effort over the utility of an optimal option. Satisficing may involve either a subjectively higher assessment of the cost of time and effort or a subjectively lower perceived benefit of the utility of an optimal solution.

In an examination of decision making in which time is considered a resource or commodity, Dar-Nimrod, Rawn, Lehman, and Schwartz (2009) presented participants with the option of sacrificing resources such as time in exchange for more options. It was found that maximizers, individuals intrinsically motivated to make the best choice possible, were more willing to sacrifice commodities like time to procure a larger choice array than were satisficers, individuals who tend to search for a satisfactory choice. These findings support the previous assertion of Schwartz and colleagues (2002) that

maximizers are more likely to engage in an exhaustive search and to expend more time and effort during the decision process.

However, because the human decision maker is often limited with regard to time, information, and processing capacity (Gigerenzer & Goldstein, 1996), decision making *in situ* frequently exhibits bounded rationality and the decision maker employs approximate methods rather than abides by rigid rules to handle most tasks (Simon, 1990). These approximate methods may involve stopping rules for information search. Stopping rules may be the product of inherent human perceptual and cognitive limitations or the result of temporal limits that are imposed at a macro-organizational level. For example, the TSA luggage screener has, on average, four seconds to view an X-ray scan of a piece of carry-on luggage and to decide whether it contains a weapon or other potentially hazardous item. With regard to stopping rules, Wickens and McCarley (2008) suggest that an operator will endorse a signal absent response when he or she perceives the effort required for additional searching to exceed the expected value of detecting the target or to exceed the expected cost of failing to detect it. The investigation of search strategies is particularly important in the luggage screening context, as operators may decide that the value of the target no longer exceeds the cost of its detection, despite the fact that the cost of a miss can be extraordinarily high. In the course of signal detection, the information search may involve looking for cues or features that indicate a potential target. The operator must assign some value to cues with regard to quantitative criteria that would indicate target presence.

The operator may discriminate sufficient information to reach the criteria threshold and endorse a signal present response. In the FSDT model, a signal present

response is allowable in the presence of uncertainty without violating the conditions necessary for optimal responding, namely $s = r = 0$ or $s = r = 1$. Schwartz and colleagues (2002) note the findings of Simon (1956), who argued that maximized or optimized decision making is generally not a viable strategy *in situ*, due to the limitations in time, information, and processing power of the human decision maker. As such, in many situations, satisficing may lead to more satisfactory outcomes than will maximizing or optimizing.

Hertwig and Herzog (2009) note that satisficing is a decision making strategy that allows for the selection of an option from a set of alternatives when all information is not known. A choice is perceived by the decision maker to be acceptable if it meets or exceeds the standards of a specified set of criteria. Satisficing is a decision making strategy that is generally effective under conditions that entail time constraint and uncertainty. In such scenarios, the decision maker does not have unlimited time or information with which to consider all possible alternatives. In such situations, it is often the case that satisficing, and not optimizing, brings the situation to a satisfactory conclusion.

Payne, Bettman, and Luce (1996) note that the information processing strategy adopted by a decision maker is contingent upon factors such as the range of alternatives, the format in which information and responses are provided, and the correlations between attributes. Such strategies may include an exhaustive search and consideration of all available information and all possible alternatives, or may involve invoking decision heuristics to expedite and simplify the decision making process. Cognitive effort and accuracy of response are important components in determining contingent decision

making behavior (Payne, Bettman & Luce, 1996). This framework for characterizing available strategies is referred to as the effort/accuracy framework, and represents the balancing of accurate decision making with conservation of limited cognitive resources.

While not referenced by Payne and colleagues (1996) in their discussion of the effort/accuracy framework, the applicability of these constructs to the examination of optimizing and satisficing decision making strategies appears plausible. Specifically, optimizing maximizes the degree of accuracy through an exhaustive information search and thorough processing of all available cues. Similarly, Creyer, Bettman, and Payne (1990) found that participants whose goal was to maximize accuracy, without an accompanying goal of minimizing effort, tended to acquire more information, expend greater search and acquisition time, demonstrate less selectivity in information processing, consider more alternatives, and exhibit greater accuracy. It is important to note, however, that optimizing as a decision making strategy or tendency engenders significant costs with regard to cognitive resources and opportunity costs, such as when time is considered as a commodity. Alternately, satisficing is a decision making strategy or tendency that often functions *in situ* under conditions of limited time, information, or information processing capacity (Gigerenzer & Goldstein, 1996; Simon, 1990). Satisficing sacrifices some degree of accuracy in exchange for the conservation of cognitive resources or opportunity costs.

Schwartz and colleagues (2002) proposed that in addition to being decision making strategies, optimizing and satisficing may represent behavioral decision making tendencies (Nenkov et al., 2008). Operators can potentially engage either a satisficing or optimizing strategy on a trial by trial basis. Alternately, operators may demonstrate a

general tendency toward either satisficing or optimizing across trials. Maximizers, or optimizers, consistently seek the optimal outcome, rather than an outcome that simply resolves an event in a satisfactory manner, as is the case with satisficers. Schwartz and colleagues developed the Maximization Scale to differentiate between decision makers who tend to maximize and those who to tend to satisfice. Subsequent research resulted in a shorter 6-item Maximization Scale better assessed the construct.

Discrimination between optimizing and satisficing in the current experimental paradigm utilizing simulated luggage screening entails an operator identifying target components that suffice with regard to categorization as potential threats, though they may fail to possess the optimal degree of information desired for indicating signal presence. The degree to which an operator is willing to endorse signal presence accompanied by uncertainty may depend on risk attitudes or such individual differences. Verplanken (1993) has noted specifically that information search and decision making strategies are moderated by features of the task and context. The strategies that an individual employs are contingent upon features of the task (e.g., task complexity, display format), the decision situation (e.g., the magnitude or potential outcomes of the decision, time constraint), and person characteristics (e.g., prior knowledge, individual differences). As such, the current study addresses components of these factors, namely varying signal characteristics and time constraint.

Time constraint

In general, research has demonstrated that high time constraint is not an optimal condition for effective decision making (Zakay & Wooler, 1984; Kerstholt, 1994), as time constraint exacerbates cognitive workload in decision making paradigms (Ordóñez

& Benson, 1997). Keinan (1987) found that individuals under time-pressure-induced stress tended to make decisions rapidly before all available information or alternatives were provided, leading to the adoption of one early decision option to the exclusion of all others. The detrimental effects of this premature closure are exacerbated by nonsystematic scanning, whereby a poorly organized consideration of alternatives and information exists. Further, attentional narrowing during scanning and information search precludes adequate consideration of the alternatives that are considered (Keinan, 1987). Ben Zur and Breznitz (1981) found that time constraint has been shown to decrease the amount of time an individual spends processing individual pieces of information. The processing that does occur tends to be more discriminating under time constraint. Individuals under time constraint tend to alter decision strategies toward an attribute-based style of processing that entails narrowly processing one single attribute of the decision problem before considering a second attribute (Payne, Bettman, & Johnson, 1988).

Additionally, Shanteau and Stewart (1992) have found that under high time constraint both novices and experts tend to be influenced by irrelevant information and employ heuristics or mental shortcuts due to an inability to cope with uncertainty. Although heuristics can be adaptive in some situations, there are other circumstances wherein heuristic-based decision making can lead to serious errors (Tversky & Kahneman, 1974). Much previous research has shown that individuals tend to accelerate information search under time constraint while utilizing the same search patterns. Payne, Bettman, and Johnson (1988) note an exception, whereby participants demonstrated a trend toward different search patterns under high time constraint. Payne et al. (1988)

indicate that information acquisition behavior may change under time constraint, which in turn leads to changes in information use and degraded decision quality. However, Rothstein (1986) attributes degraded decision making performance under time constraint to reduced consistency rather than changes in decision strategies. Generally, data from experimental paradigms examining time pressure due to imposed time constraints or deadlines demonstrate poorer decision making performance. This may occur in exogenously imposed time constraint conditions in the form of degraded search patterns, reduced and narrowed information processing and consideration of alternatives, and increased attention to and reliance on irrelevant information, which may contribute to the employment of heuristics to reduce cognitive effort.

It is also important to consider an alternate type of time constraint that occurs both in experimental paradigms and *in situ*. As an alternative to time constraint imposed by fixed-interval search, time constraint can also exist in the form of opportunity costs of delay. Opportunity costs of delay may involve lost opportunities or reductions in payoffs from the most accurate decision (Payne, Bettman, & Luce, 1996). Eisenhardt (1993) notes that when time constraint is the result of opportunity costs, an operator's decision making predicament is a function of the potential for errors resulting from decisions made too swiftly and the reduced effectiveness of decisions made too slowly. In some scenarios, such as the nuclear power plant example discussed by Eisenhardt, accurate decisions decrease in utility value as a function of delay in decision making.

Consideration of opportunity costs of delay might also involve the previous discussion of time as a commodity. An individual may be tasked with completing a task for a certain period of time; for example, a luggage screener may examine luggage items

for an eight hour work shift. In this scenario, the opportunity cost of delayed decision making for each item is not the operator's own time necessarily, as he or she will be at work for eight hours regardless, but rather may entail costs imposed at the macro-organizational level because of the ensuing passenger delays. As such, there may be a man-hours per unit time constraint imposed. This is a likely contributor to the average 4 second per bag screening time available to TSA luggage screeners. Alternately, an operator may tasked with screening, for example, X number of luggage items before finishing his or her work shift for the day. In this case, the operator may engender opportunity costs in the form of reduced personal time as a result of delaying decision making and extending the task duration.

Purpose of the current study

To enhance the safety of domestic airline travel, the focus must be on improving both technology and human operators. It is important to investigate the decision making elements that contribute to operator performance in luggage screening. As there are many factors that contribute to information search and target detection efficacy, it is important that researchers continue to study variables that serve as substantive bases for decision making strategies in a high stakes environment. However, examining the execution of decision making strategies is important as well. The purpose of the current study was to examine a proposed quantitative method for discriminating between satisficing and optimizing decision making strategies, as well as examine how time constraint, signal location, and degree of signal impact decision making both individually and synergistically.

The first objective of the study was to develop a methodology for quantifying optimizing versus satisficing tendencies in decision making through direct measurement and observation. Current methodologies for assessing behavioral decision making tendencies rely on self-report, specifically Schwartz and colleagues' (2002) Maximization Scale or Nenkov and colleagues' (2008) revision to the Short Form of the Maximization Scale (e.g., Parker et al., 2007; Diab, Gillespie, & Highhouse, 2008; Tanius, Wood, Hanoch, & Rice, 2009; Bruine de Bruin, Parker, & Fischhoff, 2007).

Generally, there are a number of criticisms regarding self-report measures and data. Self-reports can vary over time due to experience, history, or maturation effects (Campbell & Stanley, 1963). Mischel (1968) notes that self-report data may involve "deliberate faking, lack of insight, and unconscious defensive reactions" (p. 236). These criticisms speak to the reliability of self-report assessments without necessarily calling into question the validity of the measure. Test-retest reliability, or, generally, the ability to replicate results, may vary based on such factors as the perceived time window of a report, employment of availability heuristics, demand characteristics of the task situation, or other cognitive or situational factors.

Endorsement of items on the Short Form of the Maximization Scale reflects the responder's self-concept of his or her tendencies toward optimizing or satisficing when making decisions. Quantitative data regarding behavioral decision making tendencies, on the other hand, is produced via computations based on observed behavior, rather than by self-report, which has implications for what the data means. For example, Hochstein, Basili, Zelkowitz, Hollingsworth, and Carver (2005) note that in a study of effort exerted in a computer-based task, measures of effort based on self-report and on recordings

generated automatically from subjects' computing environments differed significantly. In the current study, the implementation of FSDT as a means of delineating behavioral decision making tendencies provides an index of responding that can be correlated with the state of the world to examine decision making strategies and assess operator performance. This index can be generated automatically from an operator's performance on decision making tasks, and does not require or rely on inferences based on self-reported data. Because decision making behaviors and tendencies exert a powerful influence on behavioral outcomes in a variety of critical situations (Klein & Klinger, 1991), it is important to ensure that assessments are both reliable and valid, and that behavioral classifications are supported by quantitative data.

The second objective of the study was to show how time constraint and specific signal characteristics contribute to decision making. Participants were situated in either a local fixed-interval time constraint condition or a global time constraint condition. Target detection for signals of varying ambiguity and location under both time constraints were assessed. The effects of participants' maximizing or satisficing were also assessed on both a per-trial basis (per-trial decision-making strategy; within subjects variable) and as an overall general tendency (across-trials decision-making tendency; between subjects variable). The local fixed-interval condition is more analogous to *in situ* luggage screening, and functioned similarly to a control group when examining how self-terminating search (global time constraint) impacts decision making for central versus eccentric targets, and for maximizers versus satisficers. Finally, the study also examined whether critical thresholds of search duration exist beyond which additional time does not improve decision making toward more optimal performance. The study examined

whether the current average 4-second inspection duration (not including time for the luggage image to enter and exit the visual field) for TSA screeners is the optimal man-hours per unit standard for effective threat detection. This experimental paradigm also sought to identify the outer temporal boundary beyond which additional time is not productive to signal detection. The objective was the identification of an optimal inspection duration that meets both performance and macro-organizational efficiency goals.

With these considerations in mind, the following hypotheses were formulated.

Hypotheses:

1. Participants making decisions in the local fixed-interval time constraint condition will engage in satisficing more often than will individuals making decisions in the global time constraint (self-terminating) condition. Satisficing will be operationalized as a less-than-optimal response (e.g., $0 < r < 1$ when $s = 0$ or $s = 1$; $r = 0$ or $r = 1$ when $0 < s < 1$). This is postulated in line with Klein and Klinger's (1991) application of naturalistic decision making in situations involving time stress, where individuals tend to satisfice because generating and systematically evaluating a large set of alternatives would involve an investment of time not available to the decision maker. Participants making decisions in the global time constraint condition will engage in optimizing more often than will individuals making decisions in the time constraint condition. Optimization will be operationalized as an optimal response (e.g., $r = 0$ or $r = 1$ when $s = 0$ or $s = 1$, respectively).

2. Klein and Klinger (1991) note that classical decision making approaches, such as optimizing, do not address or support decision making factors such as ambiguity, vagueness, and inaccuracies. Optimizers are more likely to discount ambiguous information. Therefore, in the ambiguous signal ($0 < s < 1$) condition, participants who have satisficed will demonstrate greater sensitivity than participants who have optimized, due to satisficers having a greater response to ambiguous information, thus increasing the perceived intensity of ambiguous signals in noise as measured by the sensitivity index d'.
3. McElree and Carrasco (1999) note that more time-limited stimuli inspection durations tend to induce more liberal response criteria. Therefore, participants in the local fixed-interval time constraint condition will have more liberal response criteria than participants in the global time constraint condition, indicating that they require a lesser degree of confirmatory evidence to endorse a signal present response.
4. Wolfe, O'Neil, and Bennet (1998) examined miss rate and detection time for targets situated at different locations on a visual display and found a moderate increase in errors as targets move toward eccentric portions of the display. Participants who tend to optimize may not be susceptible to these errors to the same degree as participants who tend to satisfice; participants who optimize are more likely to conduct a thorough search of the entire display, as opposed to concentrating on central locations in line with the more efficient and less cognitively demanding satisficing approach. As such, it is hypothesized that there will be a significant interaction of across-trials decision making tendency

(optimizing versus satisficing) and target location such that participants who optimize will not have significant differences in sensitivities for targets in central versus eccentric locations. Participants who satisfice will have significant differences in sensitivities for targets in central versus eccentric locations.

5. Individuals under time constraint will tend to follow an attribute-based style of processing (Payne, Bettman, & Johnson, 1988), and therefore will narrowly process a single attribute before considering a second attribute. Further, visual search tends to first be concentrated on central locations within the display, evidenced by higher miss rates and longer decision latencies for eccentrically located targets, defined as targets located in the outer 50% area of a display (Wolfe, O'Neil, & Bennet, 1998); as a result, eccentric targets may not be perceived as having the same strength in noise as central targets and thereby will not induce an analogous response. As such, participants in the local fixed-interval time constraint condition are expected to have lower sensitivity for targets in eccentric locations (outer 50% of the display) than targets in central locations (inner 50% of the display).

CHAPTER 2

METHOD

Participants

Participants ($N = 100$) were recruited using the Old Dominion University SONA research participation system and were compensated 2 research credits, as it was anticipated that the study would take, at maximum, in the self-terminating condition, two hours to complete. Credits could be applied to mandatory or extra class credit.

The sample size for the study is based on a power analysis, conducted with the program G*Power 3.1.3, using a power of .80, with a medium effect size, at an alpha level of 0.05 (Keppel & Wickens, 2004).

Materials

Tendency to maximize or satisfice was assessed using the Short Form of the Maximization Scale, a 6-item Likert-type scale presented in Appendix A (Nenkov et al., 2008; Nenkov, Morrin, Ward, Schwartz, & Hulland, 2009). Participants agreed or disagreed with scale items using a 7-point rating scale (1 = completely disagree to 7 = completely agree). Individuals whose average rating is higher than 4 are considered maximizers and individuals whose average rating is lower than 4 are considered satisficers (Schwartz, 2004). The Short Form of the Maximization Scale has been determined to have reasonable internal consistency (Chronbach's alpha = .47) and construct validity (validity index = .22) (Nenkov et al., 2008); the authors note that although higher alpha levels indicate better internal consistency, Chronbach's alpha is directly proportional to the number of items on a scale, and therefore scales with fewer items will have lower mean alpha levels (Nenkov et al., 2008). Nenkov and colleagues

(2008) asserted that the shorter 6-item version of the Maximization Scale performs at a level superior to that of the original 13-item scale, despite a reduction in reliability and validity due to a decreased number of scale items. The Maximization Scale has been applied successfully in previous research examining self-reported tendencies toward maximizing versus satisficing (Parker et al., 2007; Schwartz et al., 2002).

The stimuli for this experiment consisted of profile images of handguns amidst other objects in luggage items. Target stimuli were created using the commercially available image morphing software Morpheus Photo Morpher v3.11 (Morpheus Software, 2009). X-ray images of handguns and non-target objects, such as power drills and hairdryers, were morphed utilizing progressively greater degrees of target category membership in 20% increments. Morpheus software allows for customization of images such that the user can determine the precise percentage of each primary image to merge together into the emergent engineered image. See Appendix B for examples of objects ranging from $s = 0$ to $s = 1$ in 20% increments of target category membership. These images of objects of varying degrees of target category membership were then inserted into x-ray images of luggage items to generate the full stimuli set (see Appendices C-E for full stimuli set, arranged by centrally located $0 < s \leq 1$, eccentrically located $0 < s \leq 1$, and $s = 0$).

Participants viewed images of three types: unequivocal signal present (16%; $s = 1.0$), unequivocal signal absent (50%; $s = 0$), and ambiguous signal (34%; $0 < s < 1$) (see Figure 6 for detailed stimuli distribution information). This distribution of signals was intended to provide sufficient instances of each signal type to allow for analyses across various factors, such as target location and degree of target category membership.

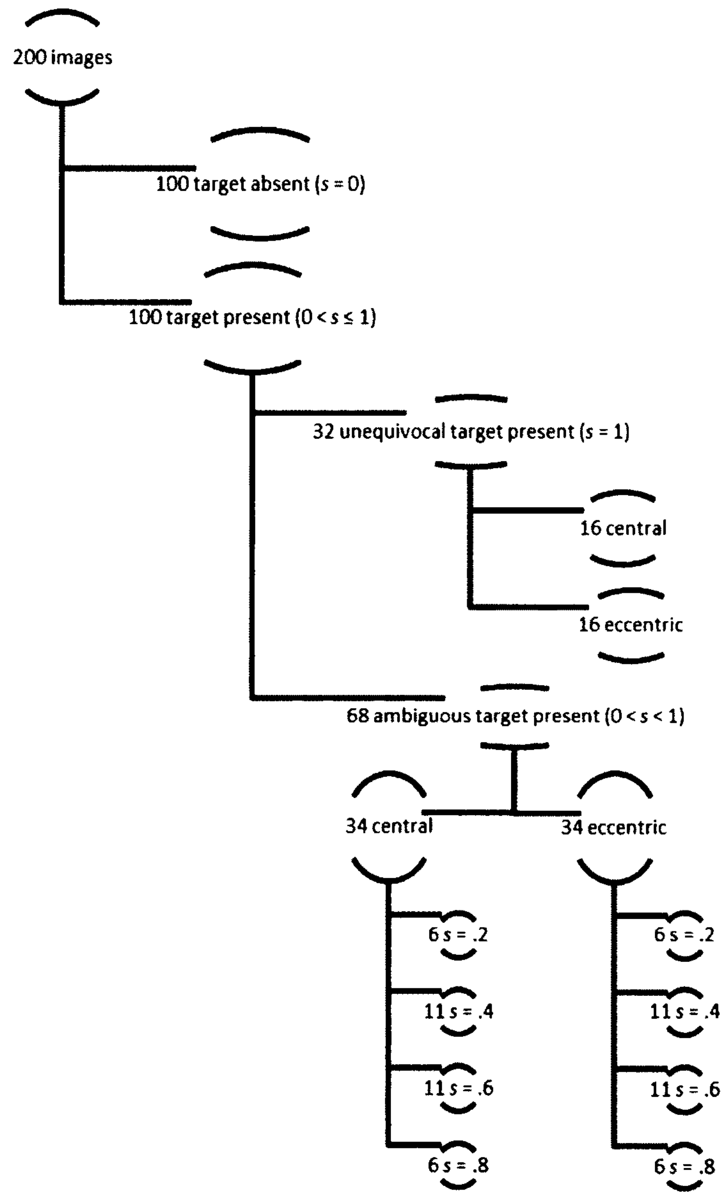

Figure 6. Stimuli distribution

Within the unequivocal signal present and ambiguous signal image categories, 50% of targets were randomly located in the central portion of the display (see Appendix C) and 50% of targets were randomly located in the eccentric portion of the display (see

Appendix D). Thackray and Touchstone (1991) examined eccentricity effects by characterizing the outer 50% of the display as the eccentric region and the inner 50% of the display as the central region for target presentation. (See Appendix E for target absent stimuli images.)

Procedure

Participants reviewed and signed an informed consent form (see Appendix F). Participants were randomly assigned to one of two time constraint conditions: global time constraint (n=50), in which participants self-terminated the information search for each x-ray image, and local fixed-interval time constraint (n=50), in which participants had 4000 ms per x-ray image for information search. Participants answered demographic questions concerning sex and race/ethnicity.

The study incorporated a 3 (signal: unequivocal present, ambiguous, unequivocal absent) X 2 (time constraint: local fixed-interval vs. global) X 2 (target location: central vs. eccentric) mixed factorial design. Degree of signal and target location were within subject factors; time constraint was a between subjects factor. Signals were classified as unequivocally present when $s = 1$, unequivocally absent when $s = 0$, and ambiguous when $0 < s < 1$. Participants interacted with a computer-based simulation of an airline luggage screening task, composed with the software ePrime, using Dell Optiplex 780 computers running the Windows 7 operating system.

Participants were tasked with deciding whether x-ray images of passenger luggage contained hazardous objects. Participants were shown examples of targets with varying degrees of target category membership (see Appendix B and Appendix G). Participants then scanned 200 images, with a 50% target presence rate ($s > 0$) for both

time constraint groups in line with previous research utilizing the simulated luggage screening paradigm (Gonzalez & Madhavan, 2011). Participants were not informed of the base rate.

Participants were randomly assigned to one of two time constraint conditions: global time constraint, in which participants self-terminated the information search for each x-ray image, and local fixed-interval time constraint, in which participants had 4000 ms per x-ray image for information search. The 4000 ms exposure time is based on an estimate from the Transportation Security Administration (TSA) as the average duration available to luggage screeners for information search in an x-ray image centered on the display screen (not including time to enter and exit the screen), and has been utilized in previous research (Wales, Anderson, Jones, Schwaninger, & Horne, 2009; Culley & Madhavan, 2011). The local fixed-interval condition was proposed to be the closest analog to search conditions *in situ*.

Participants in the global time constraint condition could see each image for as long as they wished; the image did not advance until the participant self-terminated the information search. Participants in this condition were informed that they must remain in the laboratory until their designated time slot had ended, regardless of whether they finished the experiment early. This instruction was intended to discourage participants from rushing or accelerating decision making so as to complete the experiment in a shorter amount of time with the intention of leaving the laboratory early. The experimental design was intended to preclude or reduce the effects of perceived opportunity cost time constraint. It was important that perceived time constraint,

exogenous or endogenous, was minimized to the greatest extent possible in this experimental condition.

Participants in the global time constraint condition were instructed to examine the images on the display for as long as they needed before providing a response regarding signal presence.

Participants in the local fixed-interval time constraint condition were instructed to examine the images on the display, which would automatically time out after a period of time, and to provide a response regarding signal presence. The full instructions provided to participants in each time constraint condition can be found in Appendix H.

After each image timed out (in the 4000 ms condition) or the participant self-terminated the search, the participant then entered decision responses by moving a hexagon cursor with the computer mouse above a scroll bar that ranged from "No target" ($r = 0$) to "Target" ($r = 1$) (see Figure 7). The response input was programmed such that the hexagon cursor moved freely with the mouse across the horizontal axis, but did not deviate from the horizontal axis at all regardless of vertical mouse movements. Embedded in the scroll bar but imperceptible to the participant were 100 vertical columns that allowed for a precise value of the operator response. This type of input allowed the response to assume a discrete but sensitive degree of membership in the response category. Positioning of the cursor at the extreme ends of the scale constituted $r = 0$ and $r = 1$, respectively, while intermediate responses were quantified in the range of $0 < r < 1$. Response as a near-continuous variable provides the maximum volume of available information about each discrete event as well as trends over time.

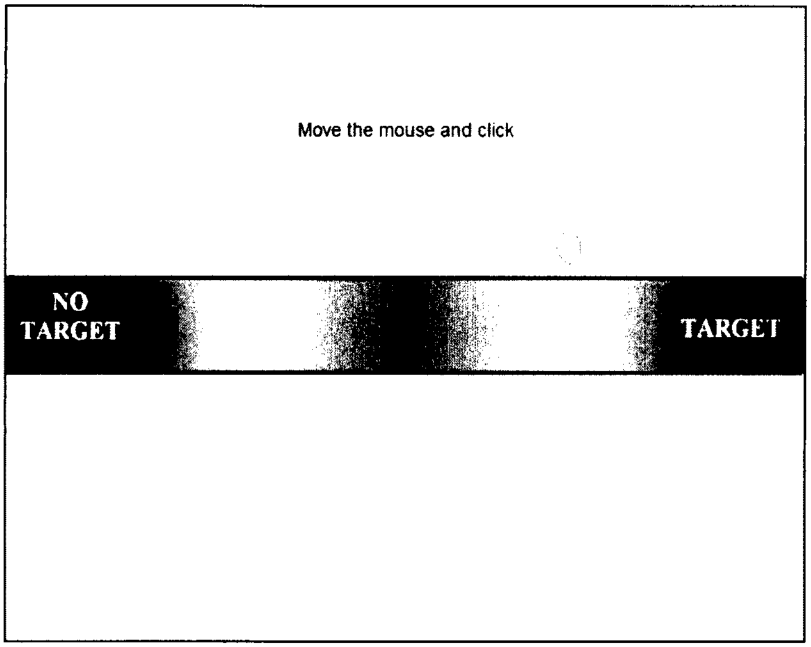

Figure 7. Operator response input

Participants completed a training block of 20 images to become familiar with targets, stimuli presentation, and response input. Participants received feedback after each decision indicating whether they were correct. During the experimental trials, participants did not receive feedback regarding whether they had made a correct decision, as knowledge of results may affect decision making behavior, and this information would not be available to luggage screeners operating *in situ.* At the end of the experiment, a short debriefing took place that explained the purpose and long-term benefits of the experiment.

CHAPTER 3

RESULTS

Glossary of variables

Across-trials decision-making tendency: data determined tendency, across the 200 trials, for each participant to satisfice or optimize. *Participant-endorsed decision-making strategy*: self-selection of optimizing or satisficing as a decision-making strategy *Per-trial decision-making strategy*: refers to trials for each participant in which the participant either optimized or satisficed; separate FSDT indices were calculated for each participant for satisficed trials and for optimized trials

Maximization Scale classification: "Satisficer" or "Optimizer" characterization based on the average of responses to questions on the Short Form of the Maximization Scale

Maximization Scale score: participant score based on the average of responses to questions on the Short Form of the Maximization Scale

Optimized response: Because of the precision of the visual analog scale with regard to allowing response inputs in increments of 1%, an r value within a ±5% interval around s constitutes an optimized response; $r \approx s$

s-r correlation: the correlation between the mean signal value and the mean response value on the visual analog scale

Satisficed response: an r value > (s + 5%) or an r value < (s + 5%) constitutes a satisficed response; r is not within a ±5% interval around s; $r \not\approx s$

Search duration: the amount of time the image to be searched for a target is available on the screen for participant viewing

Total decision time: the sum of search duration and visual analog scale response time (VAS RT)

Visual analog scale response time (VAS RT): time interval between the appearance of the decision input screen containing the visual analog scale and participants' response input

Descriptive statistics

Descriptive statistics including means and standard deviations were calculated for hit rate, false alarm rate, response criterion setting, sensitivity, visual analog scale response, and search duration, by time constraint condition, signal ambiguity, and target location. Means and standard deviations were also calculated for the Maximization Scale, task difficulty rating, and *s-r* correlation by time constraint condition (see Table 1).

Table 1. Descriptive statistics

	Global			Local			Total		
DV	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
Hit rate									
Target location									
$s = 0$	50	0.00	0.00	50	0.00	0.00	100	0.00	0.00
Central									
$s = .20$	50	0.73	0.34	50	0.56	0.43	100	0.64	0.40
$s = .40$	50	0.99	0.01	50	0.99	0.01	100	0.99	0.01
$s = .60$	50	0.99	0.02	50	0.99	0.01	100	0.99	0.01
$s = .80$	50	0.99	0.01	50	0.97	0.08	100	0.98	0.06
$s = 1.00$	50	0.96	0.06	50	0.95	0.05	100	0.95	0.06
total	50	0.93	0.07	50	0.89	0.08	100	0.91	0.08
Eccentric									
$s = .20$	50	0.65	0.41	50	0.41	0.42	100	0.53	0.43
$s = .40$	50	0.99	0.01	50	0.99	0.01	100	0.99	0.01
$s = .60$	50	0.99	0.01	50	0.99	0.02	100	0.99	0.01
$s = .80$	50	0.99	0.02	50	0.98	0.03	100	0.99	0.03
$s = 1.00$	50	0.89	0.08	50	0.87	0.08	100	0.88	0.08
total	50	0.90	0.08	50	0.85	0.08	100	0.87	0.09
Ambiguity									
$s = 0$	50	0.00	0.00	50	0.00	0.00	100	0.00	0.00
$s = .20$	50	0.69	0.33	50	0.48	0.38	100	0.59	0.36
$s = .40$	50	0.99	0.01	50	0.99	0.01	100	0.99	0.01
$s = .60$	50	0.99	0.01	50	0.99	0.01	100	0.99	0.01
$s = .80$	50	0.99	0.01	50	0.98	0.05	100	0.98	0.03
$s = 1.00$	50	0.92	0.07	50	0.91	0.06	100	0.92	0.06
Total	50	0.92	0.06	50	0.87	0.07	100	0.89	0.07

Table 1. Continued

	Global			Local			Total		
DV	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
False alarm rate									
Target location									
$s = 0$	50	0.16	0.10	50	0.11	0.12	100	0.14	0.11
Central									
$s = .20$	50	0.11	0.15	50	0.08	0.14	100	0.09	0.15
$s = .40$	50	0.74	0.18	50	0.65	0.18	100	0.69	0.18
$s = .60$	50	0.71	0.27	50	0.67	0.24	100	0.69	0.26
$s = .80$	50	0.80	0.30	50	0.68	0.37	100	0.74	0.34
$s = 1.00$	50	0.00	0.00	50	0.00	0.00	100	0.00	0.00
total	50	0.47	0.11	50	0.42	0.11	100	0.45	0.11
Eccentric									
$s = .20$	50	0.11	0.18	50	0.06	0.11	100	0.08	0.15
$s = .40$	50	0.78	0.20	50	0.63	0.23	100	0.70	0.23
$s = .60$	50	0.58	0.26	50	0.47	0.27	100	0.53	0.27
$s = .80$	50	0.79	0.29	50	0.76	0.33	100	0.77	0.31
$s = 1.00$	50	0.00	0.00	50	0.00	0.00	100	0.00	0.00
total	50	0.45	0.11	50	0.39	0.13	100	0.42	0.12
Ambiguity									
$s = 0$	50	0.16	0.10	50	0.11	0.11	100	0.14	0.11
$s = .20$	50	0.11	0.15	50	0.07	0.12	100	0.09	0.13
$s = .40$	50	0.76	0.17	50	0.64	0.18	100	0.70	0.18
$s = .60$	50	0.64	0.23	50	0.57	0.23	100	0.61	0.23
$s = .80$	50	0.79	0.25	50	0.72	0.26	100	0.26	0.26
$s = 1.00$	50	0.00	0.00	50	0.00	0.00	100	0.00	0.00
Total	50	0.53	0.11	50	0.46	0.11	100	0.49	0.12

Table 1. Continued

DV	Global *n*	Global *M*	Global *SD*	Local *n*	Local *M*	Local *SD*	Total *n*	Total *M*	Total *SD*
Sensivity									
Target location									
$s = 0$	50	0.17	0.10	50	0.12	0.12	100	0.15	0.11
Central									
$s = .20$	50	0.84	0.43	50	0.63	0.51	100	0.74	0.48
$s = .40$	50	1.73	0.18	50	1.64	0.18	100	1.68	0.18
$s = .60$	50	1.69	0.28	50	1.66	0.24	100	1.68	0.26
$s = .80$	50	1.79	0.31	50	1.66	0.41	100	1.72	0.37
$s = 1.00$	50	0.97	0.06	50	0.96	0.05	100	0.96	0.06
total	50	1.40	0.14	50	1.31	0.14	100	1.36	0.14
Eccentric									
$s = .20$	50	0.75	0.52	50	0.47	0.49	100	0.61	0.52
$s = .40$	50	1.77	0.20	50	1.62	0.23	100	1.69	0.23
$s = .60$	50	1.57	0.26	50	1.46	0.28	100	1.51	0.27
$s = .80$	50	1.78	0.29	50	1.74	0.35	100	1.76	0.32
$s = 1.00$	50	0.90	0.08	50	0.88	0.08	100	0.89	0.08
total	50	1.35	0.15	50	1.23	0.16	100	1.29	0.16
Ambiguity									
$s = 0$	50	0.17	0.10	50	0.12	0.12	100	0.15	0.11
$s = .20$	50	0.80	0.42	50	0.55	0.46	100	0.67	0.46
$s = .40$	50	1.75	0.17	50	1.63	0.18	100	1.69	0.18
$s = .60$	50	1.63	0.24	50	1.56	0.23	100	1.60	0.24
$s = .80$	50	1.78	0.26	50	1.70	0.27	100	1.74	0.27
$s = 1.00$	50	0.93	0.07	50	0.92	0.06	100	0.93	0.06
Total	50	1.27	0.12	50	1.17	0.12	100	1.22	0.13

Table 1. Continued

DV	Global			Local			Total		
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
Response criteria									
Target location									
$s = 0$	50	1.91	0.43	50	1.63	0.54	100	1.77	0.50
Central									
$s = .20$	50	0.30	0.21	50	0.45	0.33	100	0.38	0.28
$s = .40$	50	0.50	0.22	50	0.42	0.18	100	0.46	0.20
$s = .60$	50	0.52	0.25	50	0.50	0.28	100	0.51	0.26
$s = .80$	50	0.70	0.32	50	0.62	0.25	100	0.66	0.34
$s = 1.00$	50	0.12	0.04	50	0.13	0.04	100	0.13	0.04
total	50	0.43	0.12	50	0.42	0.13	100	0.43	0.13
Eccentric									
$s = .20$	50	0.38	0.29	50	0.56	0.34	100	0.47	0.33
$s = .40$	50	0.57	0.26	50	0.43	0.20	100	0.50	0.24
$s = .60$	50	0.40	0.21	50	0.33	0.16	100	0.37	0.19
$s = .80$	50	0.65	0.29	50	0.66	0.32	100	0.65	0.30
$s = 1.00$	50	0.16	0.04	50	0.18	0.04	100	0.17	0.04
total	50	0.43	0.13	50	0.43	0.14	100	0.43	0.13
Ambiguity									
$s = 0$	50	1.91	0.43	50	1.63	0.54	100	1.77	0.50
$s = .20$	50	0.34	0.22	50	0.50	0.29	100	0.42	0.27
$s = .40$	50	0.54	0.20	50	0.43	0.17	100	0.48	0.19
$s = .60$	50	0.46	0.19	50	0.41	0.18	100	0.44	0.19
$s = .80$	50	0.68	0.27	50	0.64	0.28	100	0.66	0.27
$s = 1.00$	50	0.14	0.04	50	0.15	0.03	100	0.15	0.03
Total	50	1.15	0.20	50	1.00	0.26	100	1.07	0.24

Table 1. Continued

DV		Global			Local			Total	
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
VAS									
Target location									
$s = 0$	50	16.24	10.14	50	10.78	11.54	100	13.51	11.15
Central									
$s = .20$	50	22.85	16.89	50	16.79	17.57	100	19.82	17.41
$s = .40$	50	84.31	10.56	50	79.00	10.65	100	81.66	10.89
$s = .60$	50	88.08	11.36	50	86.84	9.82	100	87.46	10.58
$s = .80$	50	95.88	6.58	50	92.47	11.80	100	94.18	9.66
$s = 1.00$	50	95.75	6.23	50	94.95	5.53	100	95.35	5.87
total	50	77.37	5.82	50	74.01	5.25	100	75.69	5.76
Eccentric									
$s = .20$	50	21.01	19.92	50	12.09	15.70	100	16.55	18.40
$s = .40$	50	86.60	11.98	50	77.75	13.72	100	82.17	13.56
$s = .60$	50	83.33	10.33	50	78.48	11.42	100	80.90	11.10
$s = .80$	50	95.63	6.41	50	94.67	8.46	100	95.15	7.48
$s = 1.00$	50	89.14	8.04	50	86.52	8.13	100	87.83	8.15
total	50	75.14	6.02	50	69.90	6.31	100	72.52	6.68
Ambiguity									
$s = 0$	50	16.24	10.14	50	10.78	11.54	100	13.51	11.15
$s = .20$	50	21.93	16.50	50	14.44	15.62	100	18.19	16.42
$s = .40$	50	85.45	10.45	50	78.38	10.57	100	81.92	11.05
$s = .60$	50	85.70	9.63	50	82.66	9.42	100	84.18	9.60
$s = .80$	50	95.75	5.63	50	93.57	7.07	100	94.66	6.45
$s = 1.00$	50	92.45	6.56	50	90.73	5.91	100	91.59	6.27
Total	50	70.80	5.29	50	66.40	5.15	100	68.60	5.64

Table 1. Continued

	Global			Local			Total		
DV	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
Search_RT									
Target location									
s = 0	50	4465.80	0.01	50	4000.00	0.00	100	4232.90	0.01
Central									
s = .20	50	3249.48	0.01	50	4000.00	0.00	100	3624.74	0.01
s = .40	50	1772.44	882.82	50	4000.00	0.00	100	2886.22	0.01
s = .60	50	2182.76	0.01	50	4000.00	0.00	100	3091.38	0.01
s = .80	50	1511.18	973.11	50	4000.00	0.00	100	2755.59	0.01
s = 1.00	50	1472.86	482.19	50	4000.00	0.00	100	2736.43	0.01
total	50	1912.74	692.24	50	4000.00	0.00	100	2956.37	1156.44
Eccentric									
s = .20	50	3898.30	0.01	50	4000.00	0.00	100	3949.15	0.01
s = .40	50	2461.63	0.01	50	4000.00	0.00	100	3230.82	0.01
s = .60	50	2658.95	0.01	50	4000.00	0.00	100	3329.48	0.01
s = .80	50	1666.67	513.36	50	4000.00	0.00	100	2833.34	0.01
s = 1.00	50	2487.18	980.58	50	4000.00	0.00	100	3243.59	0.01
total	50	2590.22	849.71	50	4000.00	0.00	100	3295.11	926.96
Ambiguity									
s = 0	50	4465.80	0.01	50	4000.00	0.00	100	4232.90	0.01
s = .20	50	3573.89	1755.24	50	4000.00	0.00	100	3786.95	1253.29
s = .40	50	2117.04	823.55	50	4000.00	0.00	100	3058.52	1109.52
s = .60	50	2420.86	962.54	50	4000.00	0.00	100	3210.43	1043.21
s = .80	50	1588.93	581.95	50	4000.00	0.00	100	2794.46	1278.91
s = 1.00	50	1980.02	643.44	50	4000.00	0.00	100	2990.01	1111.44
Total	50	3358.64	1201.52	50	4000.00	0.00	100	3679.32	904.66

Table 1. Continued

	Global			Local			Total		
DV	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
Maximization scale	50	5.02	0.88	50	5.13	0.78	100	5.07	0.82
Task difficulty rating	50	2.88	1.10	50	2.56	0.84	100	2.72	0.99
s-*r* correlation	50	0.74	0.12	50	0.78	0.07	100	0.76	0.10

Homogeneity of groups

An independent-samples t-test was conducted to compare Maximization Scale scores of participants in the global time constraint condition (M = 5.02, SD = .88) and participants in the local time constraint condition (M = 5.13, SD = .76). There were no significant differences, $t(98)$ = -.69, p = .411, 95% CI [-.44, .21], indicating homogeneity of groups for this variable.

An independent-samples t-test was conducted to compare task difficulty ratings of participants in the global time constraint condition (M = 2.88, SD = 1.10) and participants in the local time constraint condition (M = 2.56, SD = .84). There were no significant differences, $t(98)$ = 1.64, p = .159, 95% CI [-.07, .71].

Sigmoid mapping function relating signal value, *s*, to operator response value, *r*

Operator response was mapped to degree of target category membership to examine the relationship between the state of the world and operator response. As predicted (see Figure 5), the relationship followed a monotonic increasing function within the restricted domain $0 < s < 1$ (see Figure 8). This sigmoid mapping function demonstrates the significant increases in participants' estimations of target presence between s = 0 and s = .20, and between s = .20 and s = .40, with response saturation occurring at moderate levels of target presence. As ambiguous signals increased in value

beyond .40, participants consistently overestimated the degree of target presence, likely due to the high cost of a miss in the luggage screening paradigm.

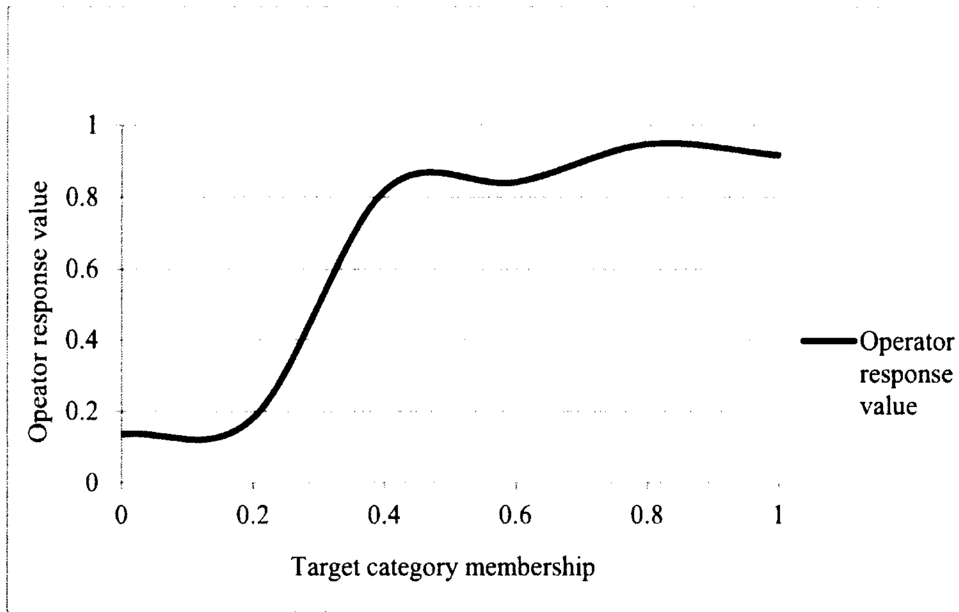

Figure 8. Sigmoid mapping function relating signal value, s, to operator response value, r

Decision-making strategy

Responses for all $s = 0$ and $s = 1$ trials were coded as either a satisficed (or less than optimal) response ($0 < r < 1$) or an optimized response ($r \approx 0$ or $r \approx 1$, respectively). Responses for all $0 < s < 1$ trials were coded as either a satisficed response ($r = 0$ or $r = 1$ or $r \not\approx s$) or an optimized response ($r \approx s$). Because of the precision of the visual analog scale with regard to allowing response inputs in increments of 1%, an r value within a ±5% interval around s constitutes an optimized response.

A 2 (time constraint condition: local vs global) x 2 (per-trial decision-making strategy: optimizing vs satisficing) mixed ANOVA on total number of per-trial decision-making strategy response types revealed a significant interaction (see Figure 9) indicating

differences between the number of satisficed and optimized responses by time constraint condition, $F(1, 98) = 6.68, p = .011, \eta^2 = .06$. Participants in the global condition (M = 88.32, SD = 37.59) satisficed more often than participants in the local condition (M = 72.36, SD = 31.83), $F(1, 98) = 5.25, p = .024$, 95% CI [77.64, 99.00]. With regard to optimized responses, the main effect approached significance; participants in the global condition (M = 75.22, SD = 24.75) optimized more than those in the local condition (M = 83.64, SD = 23.64), $F(1,98) = 3.03, p = .085$, 95% CI [68.19, 82.25

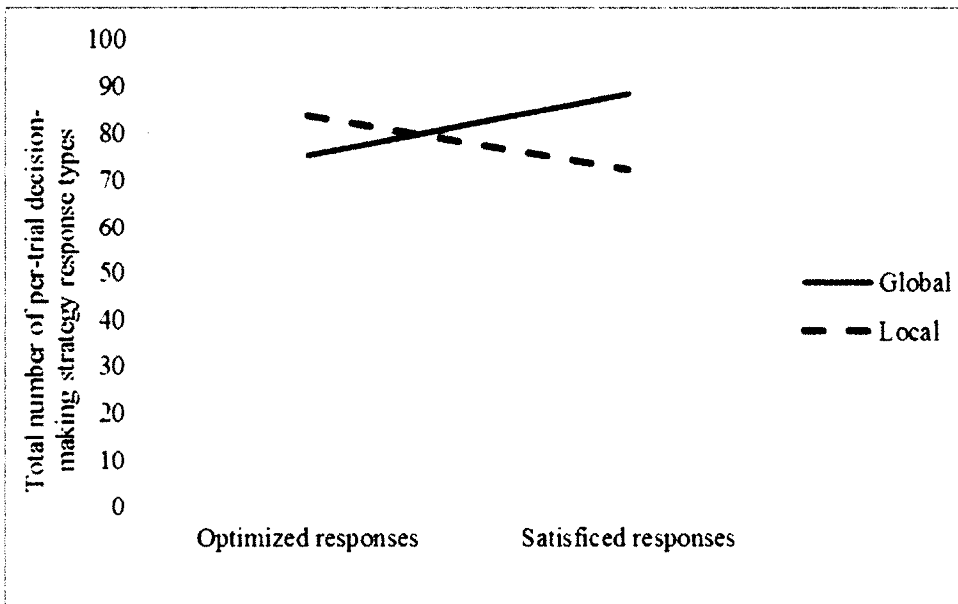

Figure 9. Interaction of per-trial decision-making strategy X time constraint on total number of per-trial decision-making response types.

A paired-samples t-test was conducted to compare sensitivities of satisficed and optimized responses to ambiguous signals. The t-test revealed that satisficed responding to ambiguous signals (M = 1.47, SD = .15) yielded greater sensitivity than optimized

responding to ambiguous signals ($M = .95$, $SD = .06$), $t(44) = 19.48$, $p < .001$, 95% CI [.47, .58].

A 2 (across-trials decision-making tendency: overall tendency toward satisficing vs overall tendency toward optimizing) X 2 (target location: central vs eccentric) mixed ANOVA was conducted to compare sensitivities for central versus eccentric targets of participants with an overall tendency to satisfice and participants with an overall tendency to optimize. The ANOVA revealed a significant main effect for target location, $F(1,98) = 18.99$, $p < .001$, partial $\eta^2 = .16$, such that sensitivities were higher for central ($M = 1.36$, $SD = .14$) compared to eccentric ($M = 1.29$, $SD = .16$) targets. The ANOVA also revealed a significant main effect for across-trials decision-making tendency, $F(1,98) = 5.86$, $p = .017$, partial $\eta^2 = .06$. Participants who satisficed ($M = 1.36$, $SD = .16$) demonstrated greater sensitivities than participants who optimized ($M = 1.29$, $SD = .15$). The interaction of across-trials decision-making tendency by target location was not significant, $F(1,98) = .404$, $p = .527$, partial $\eta^2 < .01$.

To examine the relationship between Maximization Scale classifications and participant-endorsed decision-making strategy, a chi-square test for association was conducted, $\chi^2 = 1.45$, $p = .229$, indicating that there was no statistically significant association between Maximization Scale classification and participants' endorsed decision-making strategy. Both self-endorsed satisficers and self-endorsed maximizers were equally classified as Maximizers according to the Maximization Scale.

To examine the relationship between participant-endorsed decision-making strategy and across-trials decision-making tendency, a chi-square test for association was conducted, $\chi^2 = 1.80$, $p = .180$, indicating that there is no statistically significant

association between participants' endorsed decision-making strategy and across-trials decision-making tendency.

To examine the effect of participant-endorsed decision-making strategy on search duration, a paired-samples t-test was conducted for participants in the global time constraint condition to compare search duration for participants who endorsed an optimizing strategy with search duration for participants who endorsed a satisficing strategy. Participants in the local condition were not included in the analyses because search duration was constant at 4000 ms. The t-test revealed that participants who endorsed a satisficing strategy (M = 2795.35 ms, SD = 645.33) had significantly shorter average search durations than participants who endorsed an optimizing strategy (M = 3734.17 ms, SD = 1342.28), $t(48) = -2.91$, $p = .006$, 95% CI [-1588.62, -289.01].

To examine the effect of Maximization Scale classification on search duration, an independent-samples t-test was conducted for participants in the global time constraint condition to compare search duration for participants classified by the Maximization Scale as optimizers to search duration for participants classified by the Maximization Scale as satisficers. Participants in the local condition were not included in the analyses because search duration was constant at 4000 ms. The t-test revealed no significant difference in search duration for participants classified as optimizers by the Maximization Scale (M = 3416.42 ms, SD = 1210.29) and participants classified as satisficers by the Maximization Scale (M = 2694.12 ms, SD = 983.66), $t(48) = -1.16$, $p = .253$, 95% CI [-1977.30, 532.69].

Sensitivities

A 2 (target location: central vs eccentric) X 2 (time constraint condition: global vs local) mixed ANOVA on sensitivities revealed that sensitivities for targets in central locations (*M* = 1.36, *SD* = .14) was significantly higher than sensitivities for targets in eccentric locations (*M* = 1.29, *SD* = .16), $F(1, 98) = 19.52$, $p < .001$, partial $\eta^2 = .17$. There was a significant main effect for time constraint condition on sensitivities, $F(1, 98) = 18.61$, $p < .001$, partial $\eta^2 = .16$, such that participants in the global condition (*M* = 1.27, *SD* = .12) had significantly greater sensitivity than participants in the local condition (*M* = 1.17, *SD* = .12). The interaction of target location X time constraint condition on sensitivities was not significant, $F(1, 98) = 1.04$, $p = .310$, partial $\eta^2 = .01$.

To examine the effects of signal ambiguity and time constraint condition on sensitivities, a 6 (signal ambiguity: $s = 0$, $s = .20$, $s = .40$, s = .60, $s = .80$, $s = 1.00$) x 2 (time constraint condition: global vs local) mixed ANOVA on sensitivity was conducted. The findings revealed that participants in the global condition (*M* = 1.27, *SD* = .12) had significantly greater sensitivities than participants in the local condition (*M* = 1.17, *SD* = .12), $F\,(1, 98) = 19.53$, $p < .001$, partial $\eta^2 = .17$ There was a significant main effect for signal ambiguity on sensitivity, $F(5, 490) = 730.59$, $p < .001$, partial $\eta^2 = .88$.

There was a significant interaction of signal ambiguity X time constraint on sensitivity (see Table 3 and Figure 10), $F(5, 490) = 2.70$, $p = .020$, $\eta^2 = .03$. There were significant differences in sensitivities between participants in the global time constraint condition and local condition when $s = 0$, $s = .20$, and $s = .40$, but not when $s = .60$, $s = .80$, or $s = 1.00$.

Table 2. Interaction of signal ambiguity X time constraint on sensitivity

	Global		Local				
Signal ambiguity	M	*SD*	M	*SD*	F statistic	*p*	partial η^2
$s = 0$	0.17	*0.10*	0.12	*0.12*	6.31	0.014	0.06
$s = .20$	0.80	*0.42*	0.55	*0.46*	7.77	0.006	0.07
$s = .40$	1.75	*0.17*	1.63	*0.18*	11.33	0.001	0.10
$s = .60$	1.63	*0.24*	1.56	*0.23*	2.57	0.112	0.03
$s = .80$	1.78	*0.26*	1.70	*0.27*	2.33	0.13	0.02
$s = 1.00$	0.93	*0.07*	0.92	*0.06*	2.07	0.154	0.02

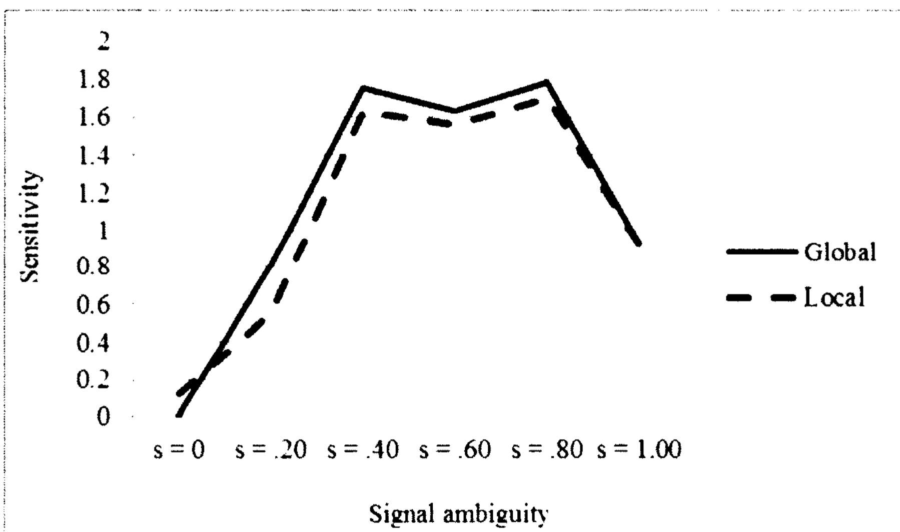

Figure 10. Interaction of time constraint X signal ambiguity on sensitivity

Response criterion settings

When examining response criteria across varying degrees of signal ambiguity, a 2 (time constraint condition: global vs local) x 6 (signal ambiguity: $s = 0$, $s = .20$, $s = .40$, s $= .60$, $s = .80$, $s = 1.00$) mixed ANOVA on response criteria revealed a significant main effect of signal ambiguity on response criteria, $F(5, 490) = 419.95$, $p < .001$, partial $\eta^2 =$ .81.

There was also a significant main effect of time constraint condition on response criteria, $F(1, 98) = 6.76, p = .011$, partial $\eta^2 = .07$, such that participants in the global condition (M = .1.15, SD = .20) had significantly higher response criteria than participants in the local condition (M = 1.00, SD = .26).

There was a significant interaction of time constraint condition and signal ambiguity on response criteria (see Table 2 and Figure 11), $F(5, 490) = 6.78, p < .001$, partial $\eta^2 = .07$.

Table 3. Interaction of time constraint X signal ambiguity on response criteria

	Global condition		Local condition				
Signal ambiguity	M	*SD*	M	*SD*	F-statistic	*p*	partial η^2
s = 0	1.91	*0.43*	1.63	*0.54*	8.4	0.005	0.08
s = .20	0.34	*0.22*	0.5	*0.29*	9.83	0.002	0.09
s = .40	0.54	*0.2*	0.43	*0.17*	8.93	0.004	0.08
s = .60	0.46	*0.19*	0.41	*0.18*	1.56	0.215	0.02
s = .80	0.68	*0.27*	0.64	*0.28*	0.52	0.475	0.01
s = 1.00	0.14	*0.04*	0.15	*0.03*	2.7	0.104	0.03

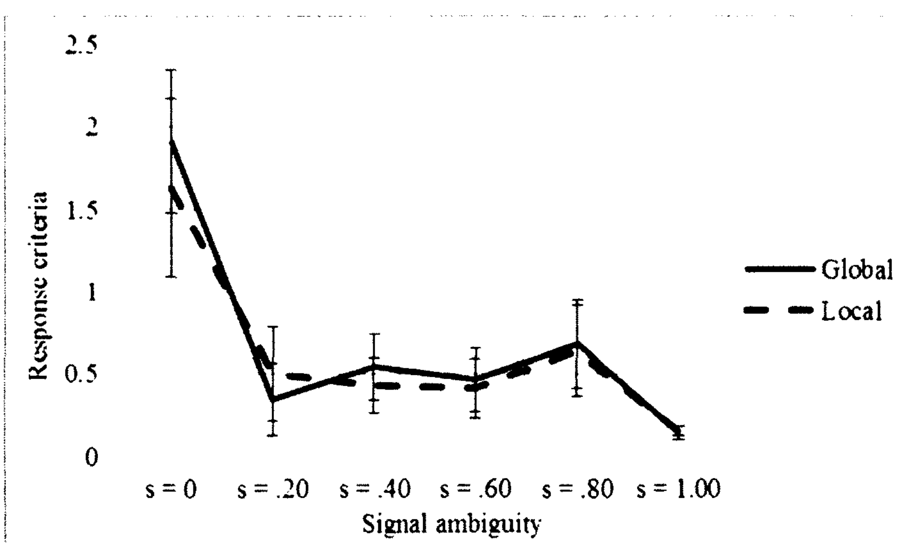

Figure 11. Interaction of time constraint X signal ambiguity on response criteria

To further explore the relationship between time constraint condition and response criteria under varying degrees of signal ambiguity, a one-way (signal ambiguity: $s = .20$, $s = .40$, s = .60, $s = .80$, $s = 1.00$) within subjects ANOVA was conducted to compare the effects of signal ambiguity on response criteria for participants in the global condition. The ANOVA on response criteria for participants in the global condition was significant, $F(5, 245) = 298.05$, $p < .001$, partial $\eta^2 = .86$. There were significant differences in response criteria between all degrees of signal ambiguity.

The one-way within-subjects ANOVA on response criteria for participants in the local condition was significant, $F(5, 245) = 149.86$, $p < .001$, partial $\eta^2 = .75$. There were significant differences in response criteria between all degrees of signal ambiguity except $s = .20$ and $s = .40$, and $s = .40$ and $s = .60$.

To examine the effects of target location and time constraint condition on response criteria in trials in which some degree of signal is present, a 2 (target location: central vs eccentric) X 2 (time constraint condition: global vs local) mixed ANOVA on response criteria was conducted. Trials in which $s = 0$ were not included in the analysis because there was no target location. The mixed ANOVA on response criteria failed to reveal a significant main effect for target location, $F(1, 98) = .40$, $p = .530$, partial $\eta^2 < .01$, for time constraint, $F(1, 98) = .04$, $p = .837$, partial $\eta^2 < .01$, or an interaction of target location X time constraint on response criteria, $F(1, 98) = .08$, $p = .775$, partial $\eta^2 < .01$. This finding indicates that the difference in response criteria across time constraint

condition found previously is driven by the inclusion of signal absent trials, which were excluded from this analysis due to the lack of target location.

Search duration

To examine the effect of signal ambiguity on search duration, a one-way within-subjects ANOVA was conducted for participants in the global time constraint condition. Participants in the local condition were not included in the analyses because search duration was constant at 4000 ms. There was a significant effect of signal ambiguity on search duration, $F(5, 245) = 86.55, p < .001$, partial $\eta^2 = .64$. Pair-wise comparisons revealed significant differences between all search durations across signal ambiguity except between $s = .40$ and $s = 1.0$.

To examine the effect of target location on search duration, a paired-samples t-test was conducted for participants in the global time constraint condition to compare search duration for targets in central locations to search duration for targets in eccentric locations. The t-test revealed that search duration for eccentric targets ($M = 2590.22$ ms, $SD = 849.71$) was significantly longer than search duration for central targets ($M = 1912.74$ ms, $SD = 692.24$), $t(49) = -9.01, p < .001$, 95% CI [-828.52, -526.45].

Self-terminating versus fixed-interval ~4000 ms search duration

To examine the effect of participant control over search duration on sensitivity, an independent-samples t-test was conducted to compare sensitivities for participants in the global time constraint condition with average search durations of 3500-4500 ms to sensitivities for participants in the 4000 ms fixed-interval local time constraint condition. The t-test revealed a significant difference in sensitivity, $t(54) = 2.77, p = .008$, 95% CI [.04, .23]. Participants in the global condition with average search durations of 3500-4500

ms (M = 1.30, SD = .09), had significantly higher sensitivities than participants in the local condition (M = 1.17, SD = .12).

To examine the effect of participant control over search duration on response criteria, an independent-samples t-test was conducted to compare response criteria for participants in the global time constraint condition with average search durations of 3500-4500 ms to response criteria for participants in the 4000 ms fixed-interval local time constraint condition. The t-test showed that response criteria for participants in the global condition with average search durations of 3500-4500 ms (M = 1.10, SD = .17) did not significantly differ from response criteria for participants in the local condition (M = 1.00, SD = .26), $t(54) = .93$, $p = .359$, 95% CI [-.12, .32].

Critical thresholds of self-terminated search duration

To determine the point beyond which additional search time matters, search durations for participants in the global time constraint condition were coded into a categorical variable in 500 ms increments between 1000 ms and 6000 ms. Participants in the local condition were not included in the analyses because search duration was constant at 4000 ms. Univariate ANOVAs of search duration on sensitivities, $F(7, 42) = .30$, $p = .951$, $\eta^2 = .05$ and on response criteria, $F(7, 42) = .32$, $p = .941$, $\eta^2 = .05$ revealed no significant effects (see Table 4).

Table 4. SDT indices by search duration in 500 ms increments

Search duration	n	Hit rate M	Hit rate SD	Response criteria M	Response criteria SD	Sensitivity M	Sensitivity SD
duration < 1000ms	0	--	--	--	--	--	--
1000ms ≤ duration < 1500ms	0	--	--	--	--	--	--
1500ms ≤ duration < 2000ms	2	0.92	*0.07*	1.12	*0.44*	1.31	*0.18*
2000ms ≤ duration < 2500ms	9	0.93	*0.04*	1.22	*0.20*	1.29	*0.14*
2500ms ≤ duration < 3000ms	9	0.91	*0.08*	1.14	*0.22*	1.24	*0.14*
3000ms ≤ duration < 3500ms	14	0.90	*0.08*	1.14	*0.22*	1.25	*0.11*
3500ms ≤ duration < 4000ms	6	0.92	*0.05*	1.11	*0.18*	1.29	*0.09*
4000ms ≤ duration < 4500ms	4	0.96	*0.01*	1.21	*0.26*	1.30	*0.13*
4500ms ≤ duration < 5000ms	4	0.93	*0.04*	1.08	*0.08*	1.28	*0.14*
5000ms ≤ duration < 5500ms	0	--	--	--	--	--	--
5500ms ≤ duration < 6000ms	0	--	--	--	--	--	--
6000ms ≥ duration	2	0.89	*0.10*	1.06	*0.06*	1.28	*0.10*
Total	50	0.92	*0.06*	1.15	*0.20*	1.27	*0.12*

Search durations for participants in the global time constraint condition were recoded into a categorical variable in 1000 ms increments between 1000 ms and 6000 ms. Univariate (search duration in 1000 ms increments) ANOVAs of search duration on sensitivities, $F(4, 45) = .12$, $p = .973$, $\eta^2 = .01$ and on response criteria, $F(4, 45) = .23$, $p = .921$, $\eta^2 = .02$, revealed no significant effects (see Table 5).

Table 5. SDT indices by search duration in 1000 ms increments

Search duration	n	Hit rate M	Hit rate SD	Response criteria M	Response criteria SD	Sensitivity M	Sensitivity SD
duration < 1000ms	0	--	--	--	--	--	--
1000ms ≤ duration < 2000ms	2	0.94	*0.04*	1.12	*0.44*	1.31	*0.18*
2000ms ≤ duration < 3000ms	18	0.94	*0.04*	1.18	*0.21*	1.26	*0.14*
3000ms ≤ duration < 4000ms	20	0.94	*0.04*	1.13	*0.20*	1.26	*0.10*
4000ms ≤ duration < 5000ms	8	0.96	*0.03*	1.15	*0.19*	1.29	*0.13*
5000ms ≤ duration < 6000ms	0	--	--	--	--	--	--
6000ms ≥ duration	2	0.93	*0.06*	1.06	*0.06*	1.28	*0.10*
Total	50	0.92	*0.06*	1.15	*0.20*	1.27	*0.12*

Regression analyses were conducted with search duration as the independent variable to determine whether self-terminated search duration predicts sensitivity or response criteria. No statistically significant linear dependence of sensitivity, $F(1, 48) = .01$, $p = .937$, $R^2 < .01$ or response criteria, $F(1, 48) = .52$, $p = .473$, $R^2 = .01$, or, on search duration was detected.

VAS response means by time constraint

To determine whether there were significant differences between mean response values across time constraint conditions, an independent-samples t-test was conducted to compare the mean VAS score of participants in the global time constraint condition and participants in the local time constraint condition. The t-test showed that participants in the global condition ($M = 70.80$, $SD = 5.29$) had significantly higher mean VAS scores than participants in the local condition ($M = 66.40$, $SD = 5.15$), $t(98) = 4.21$, $p < .001$, 95% CI [2.33, 6.47].

CHAPTER 4

DISCUSSION

The purpose of the current study was to investigate decision-making elements, such as optimizing or satisficing strategies or tendencies, that contribute to operator performance under conditions of varying time constraint, signal location, and signal ambiguity.

Decision-making strategy

The first major objective of the current study was to examine how decision making strategies impact performance. As hypothesized, across time constraint conditions, satisficing on trials with ambiguous signals (as a per-trial decision-making strategy) resulted in greater sensitivities than optimizing on trials with ambiguous signals. It was hypothesized that across time constraint conditions, participants who satisficed would have significant differences in sensitivities for targets in central versus eccentric locations, while participants who optimized would not. However, the data indicated both satisficers and optimizers had greater sensitivities for centrally located targets compared to eccentrically located targets. Previous research suggested that participants who optimize may be less susceptible to the performance decrements for eccentric targets noted by Wolfe and colleagues (1998) because they search for information more thoroughly. However, it appears that satisficing was sufficient for the discrimination of eccentric targets despite the reduced precision associated with naturalistic decision making.

These findings are in line with Klein and Klinger's (1991) discussion of decision making that involves uncertainty, ambiguity, missing data, time stress, and high stakes,

the defining features of NDM. The NDM approach involves increased flexibility in decision making and supports a reliance on heuristics, in contrast to classical or rational decision making approaches, such as optimization, which deteriorate under time constraint or when ambiguous data are being considered. Whereas classical decision making models produce optimal solutions, NDM models satisfice, generally producing satisfactory and reasonable outcomes in a more efficient and less cognitively demanding manner. Lipshitz and Strauss (1997) contend that the reliance on heuristics inherent to decision making that occurs "in the wild" can lead to more efficient and robust decision making that does not decrease in effectiveness because a decision maker can terminate information search when cues discriminate. This stopping rule eliminates the need to consider alternatives and deplete temporal resources. This assertion is supported by the findings of the current study: in the presence and the absence of local time constraint, participants had higher sensitivities when satisficing than when optimizing.

Given the impact of decision making strategy on search performance, it was also important to examine the validity and predictive power of various indices of operator strategy. In the global time constraint condition, participants who endorsed a satisficing strategy had significantly shorter average search durations than participants who endorsed an optimizing strategy. There was no effect of Maximization Scale classification on search duration; furthermore, there was no association between Maximization Scale classification or across-trials decision-making tendency and participant-endorsed decision-making strategy. These findings indicate the need for further examination of the accuracy of self-report measures with regard to capturing tendencies or strategies in applied decision making involving ambiguous signals. These findings are suggestive of

the need for future research regarding the methods for classifying operators' decision making strategies. This is of particular importance given previous research which asserts that a satisficing approach supports more effective performance in naturalistic decision situations.

Time constraint

The second major objective of the study was to examine how time constraint impacts decision making. Participants making decisions in the local time constraint condition were expected to satisfice more often than participants making decision in the global time constraint condition. However, despite having more time available to conduct a comprehensive search, participants in the global time constraint condition who were able to self-terminate information search tended to engage in a satisficing decision making strategy, whereas participants who conducted their information search at externally imposed 4000 ms intervals optimized more frequently. Overall, participants in the global condition had significantly higher mean response values on the VAS than participants in the local condition. Over-responding to a signal would result in a response that had full membership in the hit category, but would also have membership in the false alarm category. At the same time, misses would decrease. This is important given their high cost, but is likely to degrade operator efficiency and work against the TSA's aim of keeping passenger wait times below ten minutes (Shea & Morgan, 2007).

Participants in the global condition had higher sensitivities than participants in the local condition. This finding may be a function of the tendency characteristic of satisficing, the dominant characteristic of participants in the global condition. Such participants discriminate a single cue, rather than engage in a comprehensive search that

examines all dimensions of the decision situation (Lipshitz & Strauss, 1997). The more frequent satisficing in the global condition may have driven the effect that the minimal target category attributes of low *s*-value targets were discriminated and participants endorsed a greater degree of target presence for these targets. Additionally, time constraint may have altered the search behaviors of participants in the local condition toward reduced sensitivities, resulting in degraded effectiveness. Rothstein (1986) has asserted that decision making performance is degraded under time pressure not due to changes in decision strategy, but rather as a result of reduced consistency in scanning behaviors.

When the effect of time constraint on sensitivity was examined across varying degrees of signal ambiguity, significant differences in sensitivities were found only between time constraint groups for lower signal values. This suggests that perceived time constraint, as present in the local condition, is less problematic when signals have greater degrees of target category membership. For ambiguous signals with a lower degree of target category membership, the ability to self-terminate search presumably enhanced participants' ability to distinguish a signal from noise in the global time constraint condition. For the local time constraint condition, overreliance on inadequate or ambiguous information under time pressure may have weakened information processing abilities and degraded sensitivities (Madhavan & Gonzalez, 2006). This phenomenon could have significant implications for signal detection tasks that include targets that have unique or novel configurations or when the full member set of targets in a category is unknown. These characteristics are particularly pertinent to explosive devices (Evans, 2005).

As hypothesized, overall, participants in the local condition had more liberal response criteria than participants in the global condition. This finding is likely driven by the phenomenon whereby time pressured individuals spend more time evaluating the negative consequences of decisions (Ben Zur & Breznitz, 1981); this phenomenon may have increased the salience of the high cost of a miss in the luggage screening paradigm, which in turn would induce more liberal responding. When examined across varying degrees of signal ambiguity, it was found that there were only significant differences in response criteria between time constraint groups when $s = 0$, $s = .20$, and $s = .40$. However, when the effects of target location and time constraint on response criteria were examined using only signal-present trials, the main effect for time constraint was not significant. Therefore, readers should interpret the initial finding with caution, as it appears that differences in response criteria for signal absent trials drove the initial effect.

Within each time constraint condition, there were differences in response criteria as a function of signal ambiguity. Participants in the local time constraint condition had significant differences in their response criteria toward the endpoints of the signal continuum, but there were no significant differences in response criteria between $s = .20$ and $s = .40$, and $s = .40$ and $s = .60$. Participants in the global time constraint condition had significant differences in their response criteria across all degrees of signal ambiguity. Given the lower sensitivities of participants in the local condition, they may have focused on the endpoints of the signal continuum and response scale, and may have rounded off or disregarded nuances of signals in the center of the continuum. This is in line with previous research that found that individuals under time constraint tend to alter decision strategies toward an attribute-based style of processing (Payne, Bettman, &

Johnson, 1988), which entails narrowly processing one single attribute of the decision problem before considering a second attribute. Under time constraint, participants may have focused on individual attributes of the signal rather than its overall correspondence to the target category. Additionally, because participants in the local condition detected fewer signals, these findings are in line with the results found by Stafford, Szalma, Hancock, and Mouloua (2003), whereby response criteria became more liberal as the distribution of fuzzy stimuli shifted toward the non-signal end of the continuum. Participants in the global condition, given their higher sensitivities, may have been more likely to discern varying degrees of signal presence; this is because only a single discriminating cue, rather than a more comprehensive target category match, is required to endorse signal presence when satisficing (Lipshitz & Strauss, 1997).

Participants in the global condition had shorter search durations compared to the 4-second fixed interval local condition. In trials where $s \geq .20$ and targets were centrally located, participants in the global condition had average search durations of 1912.74 ms, approximately half the duration of the 4000 ms fixed-interval search duration of participants in the local condition. For eccentrically located targets where $s \geq .20$, participants in the global condition had average search durations of 2590.22ms, approximately 65% of the 4000 ms standardized interval of participants in the local condition. Participants engaging in a search that self-terminates when a discriminating cue is discerned ostensibly completed the search in approximately half the time required for an exhaustive search in which all items in the search set were examined. This is in keeping with research findings that, on average, during target search a target will be

located roughly halfway through the search, and information search and processing can then be terminated (Van Zandt & Townsend, 1993).

Signal location

A further objective of the study was to examine how signal location impacts decision making. It was hypothesized that participants in the local time constraint condition would have lower sensitivities for targets in eccentric locations compared to central locations. In fact, participants in both the global and local time constraint conditions had higher sensitivities for targets located in the central portion of the display than targets in the eccentric portion of the display. The systematic reduction in signal detection effectiveness for eccentrically located targets is problematic, as it may generate predictable vulnerabilities in critical visual search tasks.

For participants in the global condition, search duration for eccentric targets was significantly longer than search duration for central targets. These results are in line with the findings of Thackray (1990), Wolfe, O'Neil, and Bennet (1998), and Schroeder, Stern, Stoliarov, and Thackray (1994), who also found a moderate increase in errors and extended decision latencies for targets located in eccentric, compared to central, regions of the display.

Previous research has examined the effect of target location on signal detection accuracy and search durations or decision latencies (*e.g.*, Thackray, 1990; Wolfe, O'Neil, & Bennet, 1998; Schroeder et al., 1994). However, there appears to be a dearth of research regarding the effect of target location on sensitivity and response criteria. The current results did not show an effect of signal location on response criteria. Schroeder and colleagues (1994) assert that operators have a tendency to neglect the eccentric

region of a display; the current data support the assertion that it is likely that an attentional component, rather than a decision making bias, that drives the decrease in detectability of eccentrically located targets. Participants in the current study had overall higher sensitivities for targets located in the central, compared to eccentric, portions of the display, suggesting differences in the psychophysical ability to detect targets approaching peripheral regions of the display.

Signal ambiguity

Also of interest in the current study was the impact of signal ambiguity on signal detection. As predicted (see Figure 5), the relationship between the state of the world and operator response followed a monotonic increasing function within the restricted domain $0 < s < 1$, with the saturation point of the monotonic curve occurring at moderate levels of target presence (see Figure 8). As ambiguous signals increased in value beyond .40, participants consistently overestimated the degree of target presence, likely due to the high cost of a miss in the luggage screening paradigm. This in turn caused a saturation in r beyond this threshold of signal presence. When $s = 1$, however, there was a significant decrease in r, likely driven at least in part by participants' tendency toward satisficing.

Participants in the global time constraint condition demonstrated significant differences in response criteria across all degrees of signal ambiguity, and participants in the local time constraint condition demonstrated differences in response criteria toward the endpoints of the signal continuum. Although the differences among response criteria were significant, there was a trend toward relative stability within the restricted domain $0 < s < 1$, as compared to the more dramatic shifts in response criteria when $s = 0$ or $s = 1$. This finding indicates that although participants were less likely to endorse a complete

target absent ($r = 0$) or present ($r = 1$) response, their decision-making biases were dramatically more conservative when $s = 0$ than when $s > 0$; this phenomenon occurred despite a propensity to endorse some degree of target presence when $s = 0$. Likewise, although signals with full target category membership were consistently underestimated, response criteria were notably more liberal when $s = 1$. This produced an interesting phenomena whereby participants had both remarkably liberal response criteria and an 8% miss rate when $s = 1$.

Across time constraint conditions, there was a significant effect of signal ambiguity on sensitivity. Participants had the greatest sensitivity for ambiguous signals with moderate to high degrees of target category membership ($.40 \leq s \leq .80$), indicating that this range of target category membership was most conducive to participants distinguishing a signal in noise. Sensitivity decreased for signals with low target category membership ($s \leq .20$) and complete target category membership ($s = 1$). The decrease in sensitivity when $s = 1$ may be partially attributable to the miss proportions resulting from the underestimation of signal value when the signal had full target category membership, as calculated using FSDT. As hypothesized, satisficed responses to ambiguous signals ($0 < s < 1$) yielded greater sensitivities than did optimized responses to ambiguous signals. Further, there were significant differences in sensitivities between participants in the global time constraint condition and local time constraint condition. Participants in the global condition had significantly greater sensitivities for low s-value signals compared to participants in the local condition. This finding indicates that detection of signals with lower degrees of target category membership may be further degraded by perceived time

constraint than would detection of signals with greater degrees of target category membership.

Reduced sensitivity coupled with degraded scanning behaviors under time pressure, as proposed by Rothstein (1986), may be particularly problematic given that the full member set of weapons in the aviation security domain is unknown (Evans, 2005) and potentially dangerous targets may take a variety of novel forms that only partially belong to target categories (Bravo & Farid, 2004). There was a significant effect of signal ambiguity on search duration for participants in the global time constraint condition, such that there was a general trend toward decreasing search duration as *s* increased in degree of target category membership. The findings regarding search duration are in line with dual-process theory of automaticity, whereby peak detection performance and search durations will be achieved when targets are consistently mapped and do not function as distractors (Schneider & Shiffrin, 1985). Participants may have been able to engage in more intuitive, and thus faster, decision making when responding to targets with higher values of *s* due to connotations between targets that more closely resembled firearms and their risk valuations as potential threats. This association would function as higher *s*-valued presentations always serve as targets and never as distractors, while lower *s*-value presentations are inherently more ambiguous and thus may not engender automatic processing with regard to target category membership.

Critical thresholds of self-terminated search duration

A further objective of the current study was the examination of potential critical thresholds of search duration beyond which additional time did not improve performance. To address this research question, participant search durations for participants in the

global condition were recoded as a categorical variable into both 500 ms and 1000 ms increments. There was no significant effect of self-terminated search duration on sensitivity or response criteria. Regression analyses of sensitivity and response criteria, respectively, on search duration revealed no relationship.

The data from the current study did not support a critical threshold for optimal decision-making performance or an outer temporal boundary beyond which additional time is not productive to signal detection. Additionally, the results suggest that required minimum search durations may be overestimated given equitable detection performance when durations were as short as 1000-2000 ms. This analysis was intended to examine whether the current average 4-second inspection duration for TSA screeners is an optimal or even sufficient man-hours per unit standard for effective target detection, and to identify an optimal inspection duration that meets both detection performance and macro-organizational efficiency goals. However, the data did not support the definition of an optimal inspection range, and instead suggested that temporal factors other than duration, such as operator control over search time, may exert a stronger impact on signal detection.

Self-terminating versus fixed-interval ~4000 ms search duration

Given the nonsignificant findings regarding the effects of self-terminating search on search performance, it was thus of interest to examine additional temporal factors that contribute to signal detection performance. To examine the effect of participant control over search duration, participants in the global time constraint condition with average search durations of 3500-4500 ms were compared with participants in the local time constraint condition, who had fixed-interval search durations of 4000 ms. Participants in

the global time constraint condition with ~4000 ms search durations had significantly higher sensitivities, indicating an effect of participant control over search duration. There were no significant differences in response criteria.

The finding of significant differences in performance between participants in the global condition with ~4000 ms search durations and participants in the 4000 ms local condition is interesting to consider in light of the findings of Harbison, Hussey, Dougherty, and Davelaar (2012) in a study examining memory search and recall. After learning lists of various lengths, participants were charged with recalling items for either a fixed-interval duration or a self-terminating duration. Harbison and colleagues did not find significant differences between the number of items retrieved in the open-interval versus fixed-interval conditions, indicating that participants' decisions to terminate memory search did not impact recall rates for list items. Although participants did not perform significantly better with regard to total number of items recalled in the self-terminating condition, they were able to retrieve the same amount of information via memory search in a shorter duration. This finding indicates a more efficient person-hours-per-item parameter for participants in the self-terminating condition. Similarly, in the current study, participants in the global time constraint condition, analogous to the open-interval condition in the Harbison and colleagues study, performed better than participants in a fixed-interval condition when viewed in terms of person-hours per item. Participants in both the current study and the study conducted by Harbison and colleagues demonstrated shorter durations for task performance when provided with the opportunity to self-terminate search; however, an added complexity in the current study is the finding that participants in the global time constraint condition achieved

significantly better signal detection in shorter search intervals compared to participants in the 4-second fixed-interval time constraint condition.

Harbison and colleagues (2012) propose that alternative temporal factors to duration may exert a significant impact on performance, but limit their explanation to differences in stopping thresholds in self-terminated and experimenter-terminated search. Data from the current study support the conclusion that duration alone does not determine performance. The current study indicates that type of time constraint—global versus local—exerted a significant impact on performance. In light of the significant differences across time constraint conditions when search duration was relatively equivalent, it was of interest to explore an explanation beyond differences in stopping thresholds.

One such explanation may be the role of perceived time constraint, relative to actual *in situ* time constraint. De Donno and Demaree (2008) examined the role of real versus perceived time constraint in a between-subjects design study in which participants were informed that the decision time interval either was or was not sufficient to learn and complete the Iowa Gambling Task. De Donno and Demaree found that participants who were led to believe that the allotted time interval was sufficient to complete the task performed significantly better than participants who were led to believe that the allotted time interval was insufficient and thus experienced increased perceived time constraint. The authors assert perceived time constraint results in simplifying strategies, such as systematically overweighting negative evidence and attending to fewer data dimensions (Wright, 1974), as well as a reduction in information search and processing, a failure to consider important data, and poor judgments (Ahituv, Igbaria, & Sella, 1998). Participants in the local time constraint condition of the current study were not directly

informed that the search intervals they were allotted for information search were insufficient; however, the automatic nature of image advancement was intended to induce a sense of time constraint and the need to cope with limited time (Ordóñez & Benson, 1997). These effects are proposed to have contributed to the degraded performance demonstrated by participants in the local time constraint condition.

An alternative explanation for the current finding that participants in the global time constraint condition demonstrated superior performance may involve perceived control over time, given that participants who were able to self-terminate information search were not subject to automatic image advancement. Perceived control over time has been noted as a stress coping strategy and has resulted in better performance and problem solving abilities in a sample of college students (Nonis, Hudson, Logan, & Ford, 1998). Likewise, perceived control over time has also been positively correlated with academic performance (Macan, Shahani, Dipboye, & Phillips, 1990; Britton & Tesser, 1991). Macan (1994) examined perceived control over time in workers at a social service agency and a correctional facility, and found a significant negative correlation between perceived control of time and stress; workers who experienced greater perceived control over time reported decreased stress. Schuler (1979) has proposed that decreased stress results in increased efficiency and effectiveness. As such, it is postulated that perceived control over time contributed to the superior performance of participants in the global time constraint condition in the current study, who were able to exercise time management during task performance, compared to participants in the local time constraint condition, who could not take an active role in the progression of information displays. Given the achievement of better performance outcomes, with regard to sensitivities, over shorter

search durations by participants in the global condition, the current findings suggest that future research examine the suitability of self-terminating searches for achieving the dual goals of superior signal detection performance, so as to maximize safety, and increased efficiency, so as to satisfy macro-organizational constraints.

CHAPTER 5

CONCLUSION

To ensure aviation safety, there must be a focus on improving the human and technology elements of airport security. As such, it is important to investigate the decision making elements that contribute to efficient and effective operator performance of information search and target detection. The method applied to evaluate operator performance can have a significant impact on the volume of information gleaned from assessments regarding operator characteristics in occupational tasks involving signal detection. Traditional, crisp SDT evaluations may fail to account for the complexity of the true state of the world, given that targets may be unequivocally present or absent, may be only partially observable or discriminable, or may have varying degrees of target category membership. FSDT indices may better reflect operator performance in the presence of ambiguous data by documenting *s-r* mappings. A quantification of the mapping between the state of the world and operator response can provide an index of an operator's satisficing or maximizing tendency when making decisions. Current methodology for assessing satisficing or maximizing tendency involves the use of a brief self-report measure. However, the shortcomings of self-report type measures have been demonstrated in previous research (*e.g.*, Campbell & Stanley, 1963; Mayer, 2004), and data from the current study failed to reveal significant relationships between the Maximization Scale and the decision-making tendencies endorsed or demonstrated by participants. As such, the *s-r* mapping technique in the current study is proposed as a more reliable technique for capturing this behavioral element of decision making. Outcomes in critical signal detection tasks can be strongly influenced by decision making

behaviors and tendencies (Klein & Klinger, 1991); as such, it is important that strategies such as optimizing or satisficing are accounted for when considering the desired operator characteristics for occupational tasks involving the detection of critical targets.

In addition to operator characteristics that impact performance outcomes, characteristics of the signal itself may also moderate signal detection. In addition to being potentially ambiguous, critical signals may also be located in a position in the display that degrades operator detection. Because satisficing and maximizing decision making tendencies are postulated to influence the degree to which signal ambiguity and eccentric target location impact operator effectiveness, it is important to examine this person-factor in conjunction with these exogenous signal characteristics. The eccentricity effect demonstrated in both the current study and previous research is likely to be compounded by time constraint, which also moved decision making in the direction of reduced sensitivity (Thompson et al., 2008) and more liberal response criteria (McElree & Carrasco, 1999). To address these important concerns, the current study sought to examine the effects of target location, signal ambiguity, and time constraint on operator signal detection, utilizing FSDT.

An additional concern of the current study was the role of time constraint on signal detection with regard to examining a possible outer temporal boundary beyond which decision making is not moved toward more optimal performance. The effects of time constraint on signal detection are of particular importance given the current standard of an average 4000 ms inspection duration for TSA screeners examining luggage items at an average airport, and the concerns regarding operator performance expressed in repeated GAO audits. However, given large passenger volume and macro-organizational

concerns, it is unclear whether it is impractical to provide TSA luggage screeners with only global time constraints, in which they self-terminate information search for each luggage item at variable intervals, theoretically ultimately limited only by the temporal boundaries of a work shift. In such a scenario, opportunity costs of delay are absorbed at the macro-organizational level, as operator decisions made too slowly are unlikely to reduce operator effectiveness at signal detection, but are highly likely to reduce operator efficiency at processing passengers in accordance with the TSA's aim of keeping passenger wait times below ten minutes (Shea & Morgan, 2007).

To achieve this goal and minimize undue delays and passenger inconvenience, and to ensure standardized practice across the nation's airports, the TSA currently maintains the 4000 ms search duration standard. However, competing needs exist for improved operator performance and expedited passenger and luggage screening. As such, the current study examined whether there is an optimal inspection duration that provides sufficient time for information search without squandering valuable temporal resources. It was initially proposed that the imposition of an appropriate man-hours per unit time constraint, comprised of the critical threshold beyond which performance measures such as sensitivity do not improve with additional time, may serve both of these goals. However, the current research supports the notion that operator control over search duration exerts a greater impact on signal detection indices such as sensitivity than does any parameterized search duration. Because means and standard deviations can be derived for populations of effective operators self-terminating information search, it is still possible to establish temporal standards against which to measure individual operator performance. Operators who routinely exceed critical thresholds for centrally or

eccentrically located targets, respectively, during training sessions or audits may be selected for additional training to improve search strategies and decision making behaviors.

Because of the criticality of decision making in an aviation security context, it is important to examine both operator characteristics, such as maximizing and satisficing tendencies, and task characteristics, such as time constraint and the location and degree of signal. The current study sought to examine both facets of the decision making situation to support efficient and effective operator performance. As decision making is a complex process, it is essential that researchers continue to conduct comprehensive examinations of the variables that contribute to information search, target detection, and the behavioral aspects of decision execution. Future research should further address the quantification of satisficing and optimizing, as decision-making strategy impacted operator performance in the current study, as well as determine whether self-terminating search is a viable strategy for improved operator performance in visual detection tasks.

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APPENDIX A

SHORT FORM OF THE MAXIMIZATION SCALE

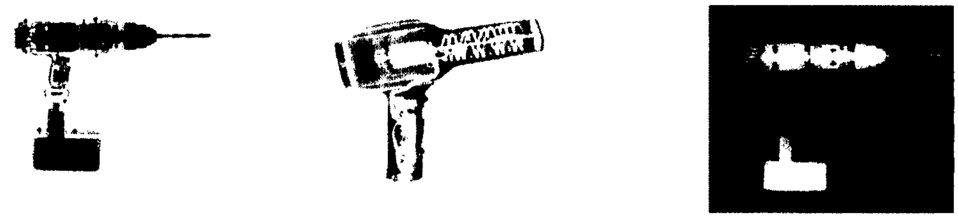
Rate each item on a scale of 1 to 7, with 1 being "completely disagree" and 7 being "completely agree."

1. When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I am relatively satisfied with what I'm listening to.
2. No matter how satisfied I am with my job, it's only right for me to be on the lookout for better opportunities.
3. I often find it difficult to shop for a gift for a friend.
4. Renting videos is really difficult. I'm always struggling to pick the best one.
5. No matter what I do, I have the highest standards for myself.
6. I never settle for second best.

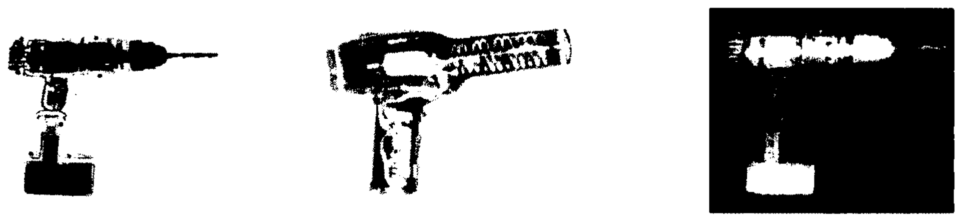
APPENDIX B

TARGET CATEGORY MEMBERSHIP EXAMPLES ($0 \leq s \leq 1$)

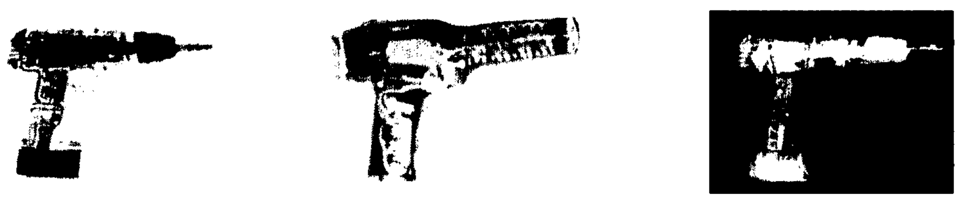
$s = 0$



$s = .2$



$s = .4$



$s = .6$

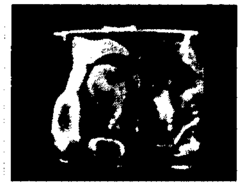
$s = .8$

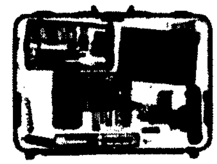
$s = 1.0$

APPENDIX C

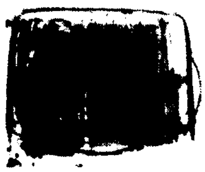
SIGNAL PRESENT STIMULI (0 < $s \leq 1$): CENTRALLY LOCATED TARGETS

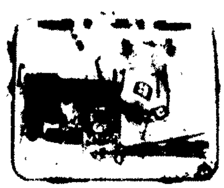

s=.2 central bag 1


s=.2 central bag 2


s=.2 central bag 3

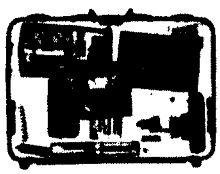

s=.2 central bag 4


s=.2 central bag 5

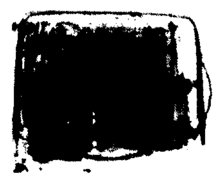

s=.2 central bag 6

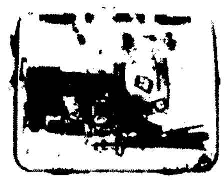

s=.4 central bag 1

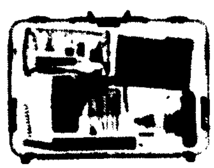

s=.4 central bag 2

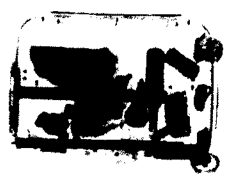

s=.4 central bag 3


s=.4 central bag 4

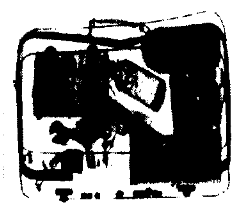

s=.4 central bag 5

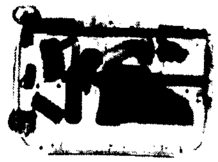

s=.4 central bag 6


s=.4 central bag 7


s=.4 central bag 8

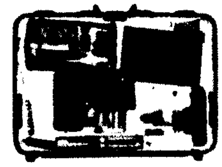

s=.4 central bag 9

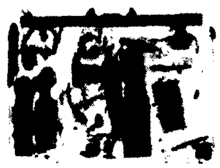

s=.4 central bag 10

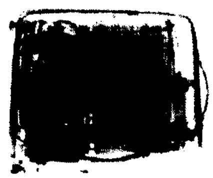

s=.4 central bag 11

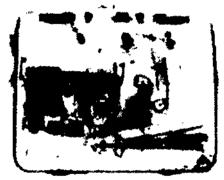

s=.6 central bag 1

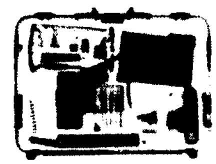

s=.6 central bag 2

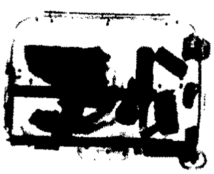

s=.6 central bag 3


s=.6 central bag 4

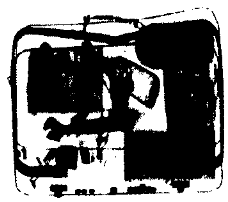

s=.6 central bag 5

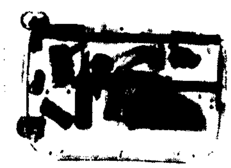

s=.6 central bag 6


s=.6 central bag 7


s=.6 central bag 8

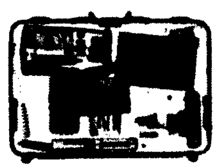

s=.6 central bag 9


s=.6 central bag 10

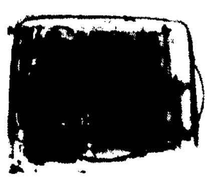

s=.6 central bag 11

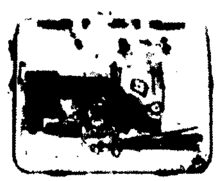

s=.8 central bag 1


s=.8 central bag 2


s=.8 central bag 3


s=.8 central bag 4


s=.8 central bag 5

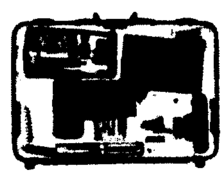

s=.8 central bag 6


s=1 central bag 1


s=1 central bag 2


s=1 central bag 3

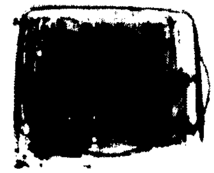

s=1 central bag 4


s=1 central bag 5


s=1 central bag 6

s=1 central bag 7

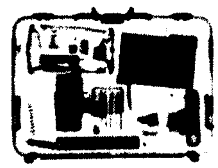
s=1 central bag 8



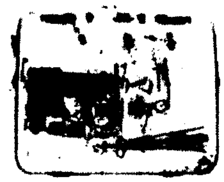
s=1 central bag 9

s=1 central bag 10

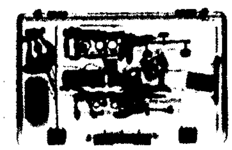
s=1 central bag 11



s=1 central bag 12

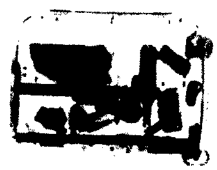


s=1 central bag 13



s=1 central bag 14

s=1 central bag 15

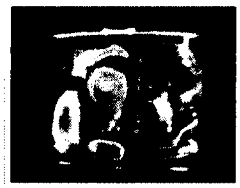


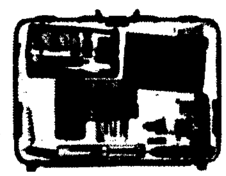
s=1 central bag 16

APPENDIX D

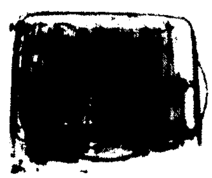
SIGNAL PRESENT STIMULI ($0 < s \leq 1$): ECCENTRICALLY LOCATED TARGETS

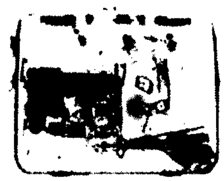

s=.2 eccentric bag 1


s=.2 eccentric bag 2

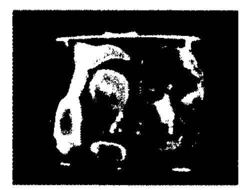

s=.2 eccentric bag 3

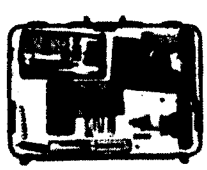

s=.2 eccentric bag 4


s=.2 eccentric bag 5

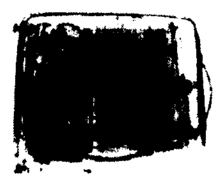

s=.2 eccentric bag 6

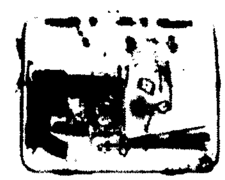

s=.4 eccentric bag 1

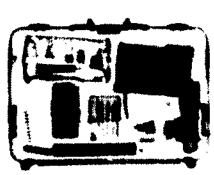

s=.4 eccentric bag 2

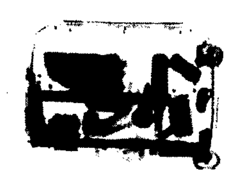

s=.4 eccentric bag 3

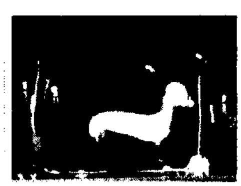

s=.4 eccentric bag 4

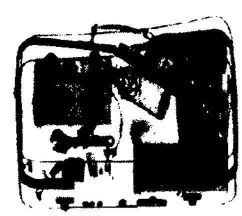

s=.4 eccentric bag 5


s=.4 eccentric bag 6


s=.4 eccentric bag 7

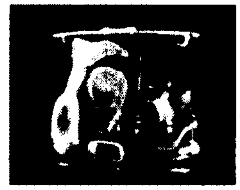

s=.4 eccentric bag 8

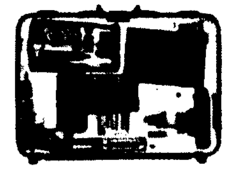

s=.4 eccentric bag 9


s=.4 eccentric bag 10

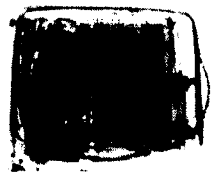

s=.4 eccentric bag 11

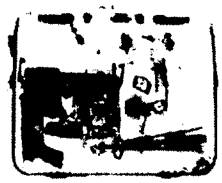

s=.6 eccentric bag 1

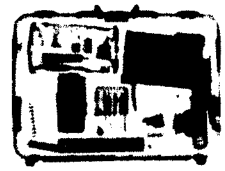

s=.6 eccentric bag 2

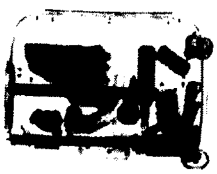

s=.6 eccentric bag 3


s=.6 eccentric bag 4

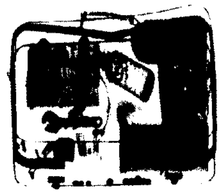

s=.6 eccentric bag 5

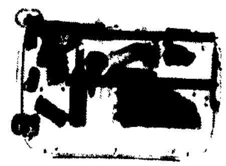

s=.6 eccentric bag 6


s=.6 eccentric bag 7


s=.6 eccentric bag 8

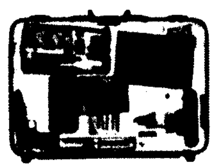

s=.6 eccentric bag 9


s=.6 eccentric bag 10

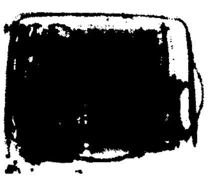

s=.6 eccentric bag 11

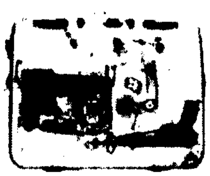

s=.8 eccentric bag 1


s=.8 eccentric bag 2


s=.8 eccentric bag 3


s=.8 eccentric bag 4


s=.8 eccentric bag 5

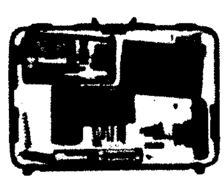

s=.8 eccentric bag 6


s=1 eccentric bag 1


s=1 eccentric bag 2


s=1 eccentric bag 3

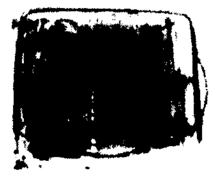

s=1 eccentric bag 4


s=1 eccentric bag 5

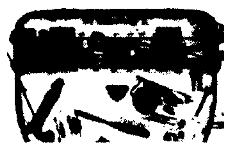

s=1 eccentric bag 6

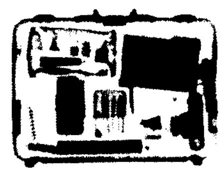

s=1 eccentric bag 7

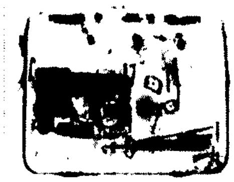

s=1 eccentric bag 8


s=1 eccentric bag 9

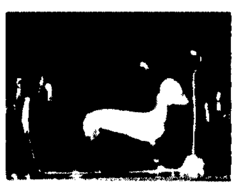

s=1 eccentric bag 10

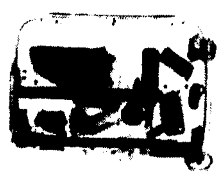

s=1 eccentric bag 11


s=1 eccentric bag 12


s=1 eccentric bag 13


s=1 eccentric bag 14


s=1 eccentric bag 15


s=1 eccentric bag 16

APPENDIX E

SIGNAL ABSENT STIMULI ($s = 0$)

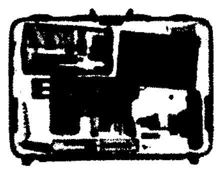
s=0 bag 1

s=0 bag 2

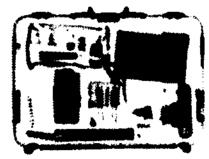
s=0 bag 3

s=0 bag 4

s=0 bag 5

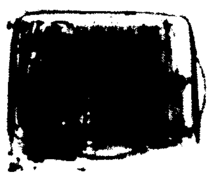


s=0 bag 6



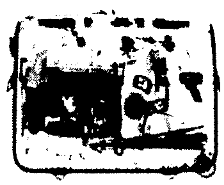
s=0 bag 7

s=0 bag 8



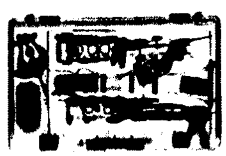
s=0 bag 9

s=0 bag 10



s=0 bag 11

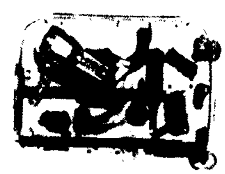
s=0 bag 12



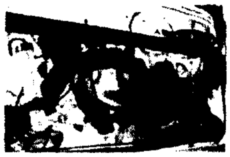
s=0 bag 13

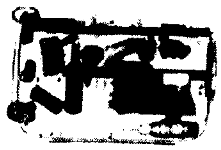
s=0 bag 14

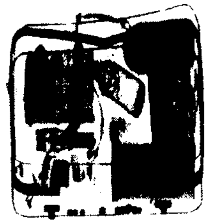
s=0 bag 15



s=0 bag 16


s=0 bag 17

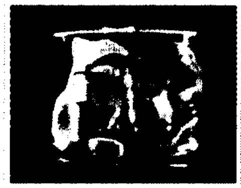

s=0 bag 18


s=0 bag 19

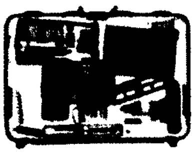

s=0 bag 20

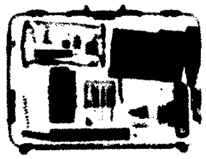

s=0 bag 21


s=0 bag 22

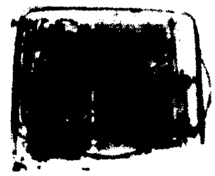

s=0 bag 23


s=0 bag 24

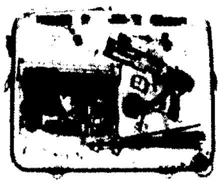

s=0 bag 25


s=0 bag 26

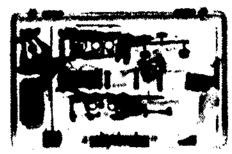

s=0 bag 27

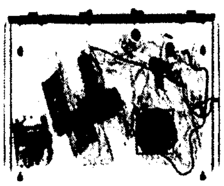

s=0 bag 28


s=0 bag 29

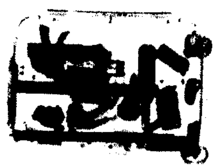

s=0 bag 30


s=0 bag 31

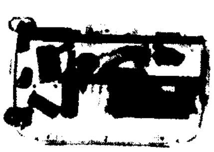

s=0 bag 32

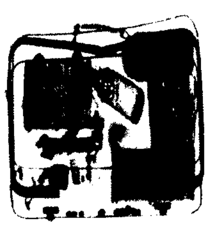

s=0 bag 33


s=0 bag 34

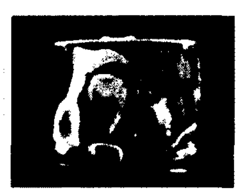

s=0 bag 35

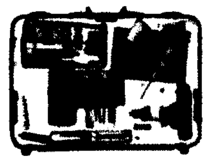

s=0 bag 36


s=0 bag 37


s=0 bag 38


s=0 bag 39


s=0 bag 40


s=0 bag 41


s=0 bag 42


s=0 bag 43

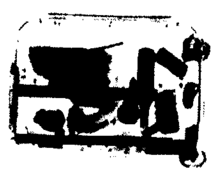

s=0 bag 44

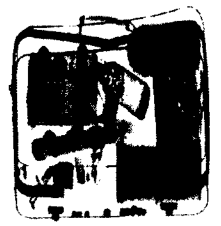

s=0 bag 45


s=0 bag 46


s=0 bag 47


s=0 bag 48

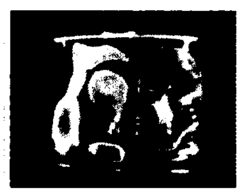

s=0 bag 49

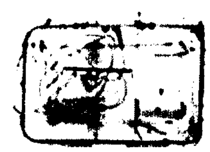

s=0 bag 50

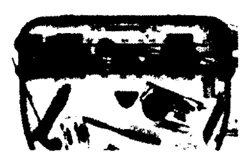

s=0 bag 51

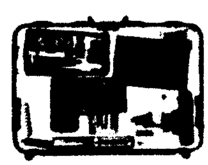

s=0 bag 52

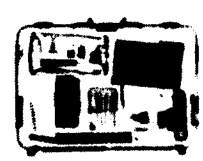

s=0 bag 53


s=0 bag 54

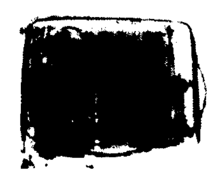

s=0 bag 55


s=0 bag 56

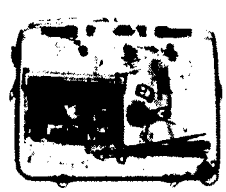

s=0 bag 57

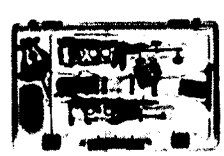

s=0 bag 58

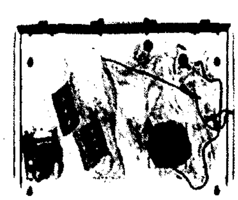

s=0 bag 59

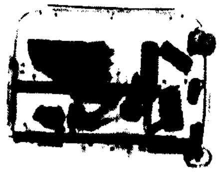

s=0 bag 60


s=0 bag 61

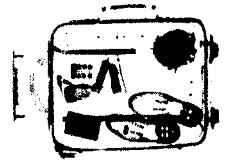

s=0 bag 62


s=0 bag 63

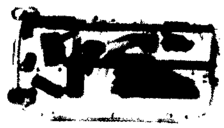

s=0 bag 64

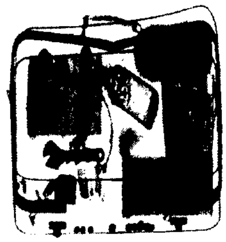

s=0 bag 65

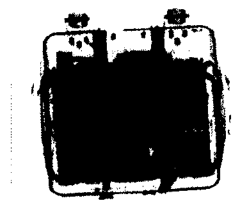

s=0 bag 66

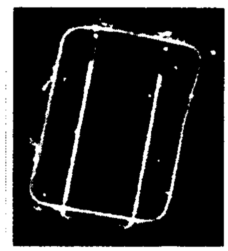

s=0 bag 67

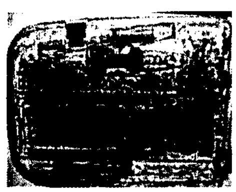

s=0 bag 68

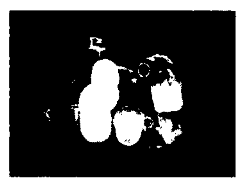

s=0 bag 69


s=0 bag 70


s=0 bag 71


s=0 bag 72


s=0 bag 73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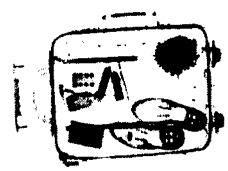
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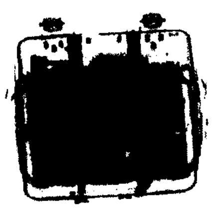
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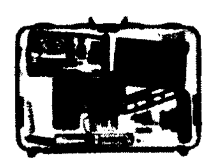
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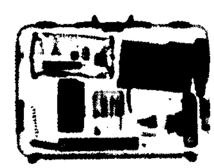
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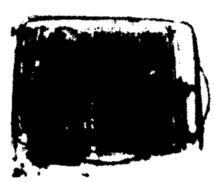
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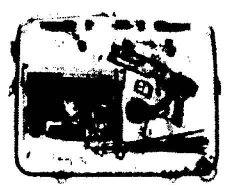
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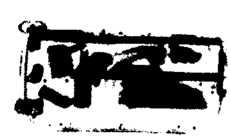
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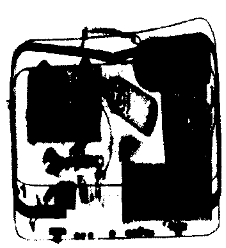
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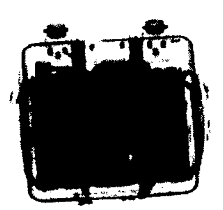
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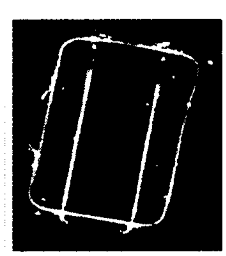
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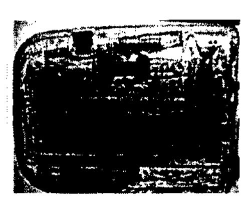
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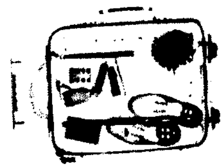
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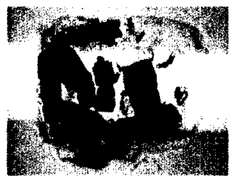
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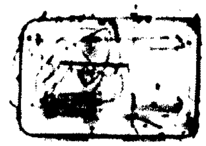
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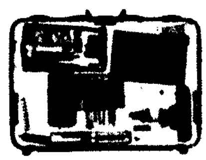
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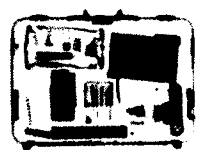
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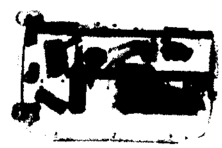
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APPENDIX F

OLD DOMINION UNIVERSITY INFORMED CONSENT DOCUMENT

PROJECT TITLE: Exogenous Factors Affecting Decision Making

INTRODUCTION

The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. The experiment will be conducted on the ODU campus in Room # 331 or Room #234 or Room #222 Mills Godwin Building.

RESEARCHERS

Responsible Project Investigator: Poornima Madhavan, Ph.D., Assistant Professor
Department of Psychology, College of Sciences, Old Dominion University

Investigator: Kimberly Culley, Graduate Student
Department of Psychology, College of sciences, Old Dominion University

DESCRIPTION OF RESEARCH STUDY

The purpose of this research is to examine how people make decisions in complex tasks with implications for homeland security.

In this experiment you will perform an airline luggage screening task, where you will have to look for dangerous objects in x-ray images of luggage, similar to what you see at an airport. On each trial, you will be presented with a piece of luggage that you will have to scan for the presence of a weapon. After the image disappears, you will be asked whether or not to pass the bag. Click on your choice. You will gain points for a correct diagnosis and lose points for a wrong diagnosis. Remember, not all bags contain targets. Please do not pause during the experiment as it is timed.

If you decide to participate, then you will join a study involving research of factors that affect human ability to visually detect targets under different conditions in the context of airline luggage screening. You will be seated in front of a computer for the entire duration of the task. You have the option at any time to cease participation without penalty. If you say YES, then your participation will last for 2 hours at Room #331 or Room #234 or Room #222, Mills Godwin Building. Approximately 175 undergraduate students will be participating in this study.

EXCLUSIONARY CRITERIA

You should be between the ages of 18 and 65 years, and have normal or corrected-to-normal vision. Also, to the best of your knowledge, you should not have any color blindness that would keep you from participating in this study.

RISKS AND BENEFITS

RISKS: The researcher has removed all linking identifiers - data will be recorded under a participant number and will not be connected to your real identity in any way. However, there is a small risk of the loss of confidentiality. As with any research, there is some possibility that you may be subject to risks that have not yet been identified.

BENEFITS: There are no direct benefits to participation. Indirectly, your participation will contribute to the development of better training solutions for luggage screeners.

COSTS AND PAYMENTS

The researchers want your decision about participating in this study to be absolutely voluntary. There is no cost to participate and no monetary payment in this study. You will receive 2 research

participation credits for participation. If you choose not to participate in research you can complete library reports to obtain the required research credits.

The primary benefit to participants is in the form of research credits awarded. Participants will receive 1 research participation credit per hour of participation in this project. These credits will be reported to faculty teaching courses in which participating students are enrolled. These credits may be used to meet required or extra credit opportunities as described in each course syllabus. They will also gain an understanding of experimental research.

NEW INFORMATION
If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY
All information obtained about you in this study is strictly confidential unless disclosure is required by law. The results of this study may be used in reports, presentations and publications, but the researcher will not identify you.

WITHDRAWAL PRIVILEGE
It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study -- at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled. The researchers reserve the right to withdraw your participation in this study, at any time, if they observe potential problems with your continued participation.

COMPENSATION FOR ILLNESS AND INJURY
If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of harm, injury or illness arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in this research project, you may contact Dr. Poornima Madhavan at 757-683-6424, Dr. George Maihafer the current IRB chair at 757-683-4520, or the Office of Research at Old Dominion University at 757-683-3460, who will be glad to review the matter with you.

VOLUNTARY CONSENT
By signing this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them:
Dr. Poornima Madhavan: (757-683-6424)
If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. George Maihafer, the current IRB chair, at 757-683-4520, or the Old Dominion University Office of Research, at 757-683-3460.

And importantly, by signing below, you are telling the researcher YES, that you agree to participate in this study. The researcher should give you a copy of this form for your records.

Subject's Printed Name & Signature	**Date**

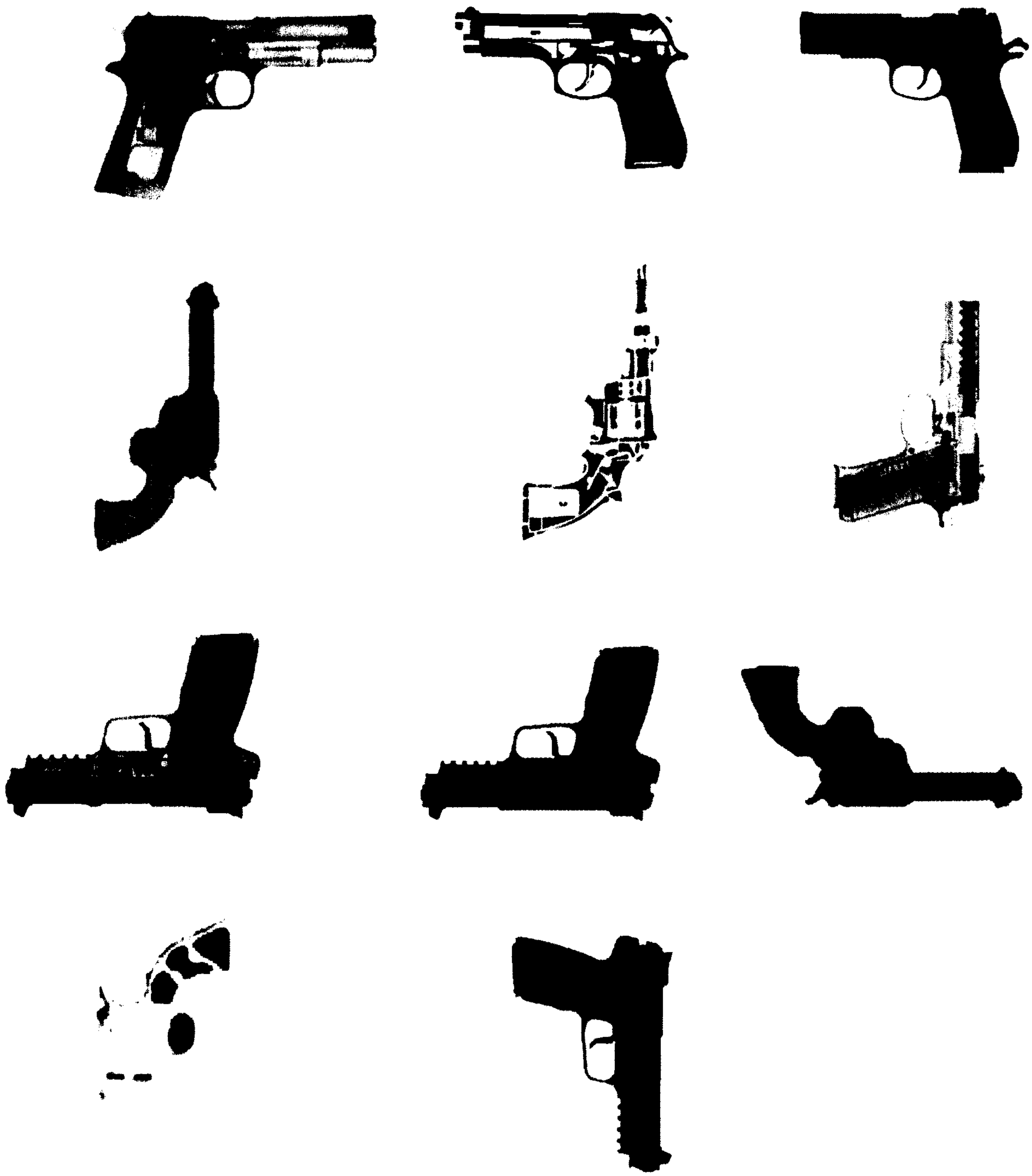
INVESTIGATOR'S STATEMENT
I certify that I have explained to this subject the nature and purpose of this research, including benefits, risks, costs, and any experimental procedures. I have described the rights and protections afforded to human subjects and have done nothing to pressure, coerce, or falsely entice this subject into participating. I am aware of my obligations under state and federal laws,

and promise compliance. I have answered the subject's questions and have encouraged him/her to ask additional questions at any time during the course of this study. I have witnessed the above signature(s) on this consent form.

Investigator's Printed Name & Signature	**Date**

APPENDIX G

TARGET CATEGORY MEMBERSHIP EXAMPLES (s = 1)



APPENDIX H

INSTRUCTIONS TO PARTICIPANTS

Participants in the global time constraint condition received the following instructions at the beginning of the task:

> "You will perform an airline luggage screening task, where you will have to look for dangerous objects in x-ray images of luggage, similar to what you see at an airport. You will scan several loads of luggage. At the beginning, you will see a set of targets on the screen. After you have looked at them and have memorized them, activate the trials by pressing the space bar.
>
> On each trial, an x-ray image of a bag will appear on the screen. You may view the image for as long as you need in order to make your decision about whether or not there is a target present in the luggage item. Please consider your decision carefully. When you are finished viewing the luggage item, press the spacebar to advance to the decision screen. After the luggage image disappears, use the response bar to indicate the degree to which the target is present in the previous image. You will gain points for a correct diagnosis and lose points for a wrong diagnosis.
>
> Remember, not all bags contain targets.
>
> Please do not pause during the experiment as it is timed. If you have any questions, please clarify them before you begin.
>
> press "Spacebar" to continue"

Participants in the local fixed-interval time constraint condition received the following instructions at the beginning of the task:

> "You will perform an airline luggage screening task, where you will have to look for dangerous objects in x-ray images of luggage, similar to what you see at an airport. You will scan several loads of luggage. At the beginning, you will see a set of targets on the screen. After you have looked at them and have memorized them, activate the trials by pressing the space bar.
>
> On each trial, an x-ray image of a bag will appear on the screen for you to view. The image will automatically time out after a period of time and advance to the decision screen. After the luggage image disappears, use the response bar to indicate the degree to which the target is present in the previous image. Please consider your decision carefully. You will gain points for a correct diagnosis and lose points for a wrong diagnosis.
>
> Remember, not all bags contain targets.
>
> Please do not pause during the experiment as it is timed. If you have any questions, please clarify them before you begin.
>
> press "Spacebar" to continue"

VITA

Kimberly E. Culley
Department of Psychology
250 Mills Godwin Building
Norfolk, VA 23529

Education

Old Dominion University, Norfolk, VA; Doctor of Philosophy, Human Factors Psychology; Expected graduation December 2013
Marywood University, Scranton, PA: Master of Arts, Industrial/Organizational Psychology; May 2009
University of Scranton, Scranton, PA; Bachelor of Science, Secondary Education; May 2004

Work Experience

Innovator- Human Factors, Kern Technology Group, LLC, Current
Human Factors Engineering Consultant, TG Labs, Inc, Current
Research Assistant, Old Dominion University, August 2010 - December 2013
Instructor, Old Dominion University, August 2011 - May 2013
Teaching Assistant, Old Dominion University, August 2010 - June 2011

Selected Publications

Culley, K.E., & Madhavan, P. (2013). Trust in automation and automation designers: Implications for HCI and HMI. *Computers in Human Behavior, 29*(6), 2208-2210. doi: 10.1016/j.chb.2013.04.032

Culley, K.E., & Madhavan, P. (2013). A note of caution regarding anthropomorphism in HCI agents. *Computers in Human Behavior, 29*(3), 577-579. doi: 10.1016/j.chb.2012.11.023

Culley, K. E., Leichty, M., & Madhavan, P. (2013). The effects of affect and inspection duration on decision time and confidence. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 57,*158-162.

Culley, K.E. (2013). Probabilistic purchasing: Consumer heuristics and biases. *2013 Neuropsychoeconomics Conference Proceedings.*

Culley, K.E. (2013). Heuristics and Biases in Climate Change Decision Making: Implications for Information Presentation and Communication. *Proceedings of the 5th Annual International Conference on Climate Change: Impacts and Responses.*

Culley, K. E., & Madhavan, P. (2012). Affect and time pressure in a simulated luggage screening paradigm: A fuzzy signal detection theory analysis. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 56,* 338-342.

Culley, K. E., Madhavan, P., Heikens, R., & Brown, J. (2011). Effects of emotional priming on visual threat detection. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 55,* 232-236.