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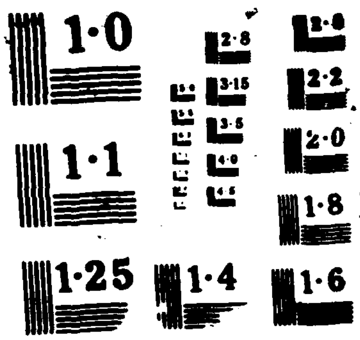
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THE EFFECTS OF COGNITIVE STYLE AND PRIOR INFORMATION ON MULTI-STAGE DECISIONMAKING (U)

ELLIOT E. ENTIN
RONALD M. JAMES
DANIEL SERFATY

ALPHATECH, INC.

JOHN A. FORESTER

ARMSTRONG AEROSPACE MEDICAL RESEARCH LABORATORY

MAY 1987

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ARMSTRONG AEROSPACE MEDICAL RESEARCH LABORATORY
HUMAN SYSTEMS DIVISION
AIR FORCE SYSTEMS COMMAND
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Drawing on the decisionmaking literature and on an initial ROC experiment a research design was formulated to investigate multi-stage decisionmaking and cognitive style in conditions of uncertainty. Subjects participating in the simulation experiment were required to discriminate between a missile attack or a missile test condition based on probabilistic imperfect information. Results from the signal detection analyses replicated the earlier effects: subjects possessing an analytic style made significantly better discriminations than subjects exhibiting a global style. ANOVA results showed that subjects held higher attack probabilities: (1) in attack conditions, (2) when missile site attack probability was high, (3) as the heat sensor range moved closer to in-missile range, and (4) with each succeeding report. All the two-way interactions proved significant as were two of the three-ways. Overall, subjects demonstrated a strong bias in favor of prior information to gauge attack probability and when that source was weak attempted to use the heat signature information. It was also possible to devise a normative-descriptive model of the subject's multi-stage decisionmaking that fit the data quite well.

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PREFACE

The work reported here was conducted between October 1984 and December 1986 by personnel of ALPHATECH, Inc., under contract F33615-82-C-0509 with the Armstrong Aerospace Medical Research Laboratory, Aerospace Medical Division, Air Force Systems Command, Wright-Patterson Air Force Base, Ohio.

Additional contributors include the following individuals: Dr. G.P. Chubb, Mr. P.E. Coughlin, Dr. W.E. Gutowski, Dr. K.R. Pattipati, Dr. N.R. Sandell, Jr., Dr. J.J. Shaw, and Mr. J.G. Wohl (ALPHATECH and ALPHASCIENCE personnel); Dr. M.L. Berbaum and Dr. D.L. Kleinman (consultants). Special thanks are extended to Dr. J.A. Forester, Capt. D.G. Leupp, Mr. D.L. Monk, Mr. W.C. Summers, Mr. M. Vikmanis, and Ms. S. Ward, currently or formerly with AAMRL/HEC, for their support and sponsorship of the work reported here and to Eileen Entin and Joan Kleinman for making subjects available.

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SECTION 1

INTRODUCTION

1.1 THE DECISION SITUATION AND THE RECEIVER OPERATING CHARACTERISTIC

In many real decision situations, there is no answer that is guaranteed to be correct. Often it is necessary to choose in such a way as to minimize negative outcome and maximize positive outcome. The strategic missile warning officer domain is certainly no exception. Under conditions of conflicting or uncertain information, the individual involved must decide whether an act is hostile or not and whether an attack has been launched. In such a situation, on the average, one cannot help but make mistakes. Acting in a way to guarantee perfect performance is all but impossible. Decisionmakers try their best to discriminate real attacks from tests, accidents, environmental disturbance, and the like. When they say "yes" and there is an attack, they are correct and this is called a "hit;" when they say "no" and there is no attack, this is called a "correct dismissal." When, however, they say "yes" and there is no attack, this is referred to as a "false alarm;" and when they say "no" and there is an attack, this is referred to as a "false dismissal" (Lindsay and Norman, 1977). False alarm and hit rates are intimately related by a relationship known as an "operating characteristic" (Green and Swets, 1966). Plotting this relationship yields an operating characteristic curve, commonly referred to as an ROC curve. ROC stands for receiver operating characteristic and was originally derived from studies of radar receivers where signals had to be discriminated from noise.

It is assumed that individuals engaged in a decisionmaking process have selected some criterion to help them decide (Lindsay and Norman, 1977). In the case of the strategic missile warning officer task, this might be whether or not an attack has been launched. The decisionmaker makes observations on incoming data and evaluates their significance. If the perceived accumulated evidence exceeds the subjective threshold (or criterion) indicating attack, then the decisionmakers report an attack. Otherwise, they say no attack. From the hit and false-alarm rates, the separation of the distributions decisionmakers must be using to make their decisions can be determined. This theoretical distance is referred to in the literature as d prime (d'). The area under the ROC curve can also provide an assessment of discrimination ability. The greater the area, the better the individuals are at making discriminations (technically, as compared to chance). Thus both d' and the area under the ROC curve can be employed as sensitive measures to contrast the effects of different treatments on individual's decisionmaking/discrimination performance.

1.2 COGNITIVE STYLE

Cognitive style can be defined as the behavioral process that individuals exhibit when engaged in the formulation or acquisition of data, analysis of data, and the interpretation of information or data for the specific purpose of decisionmaking (Sage, 1981). It has been suggested that each individual possesses a specific personality or psychological cognitive style and that each style type organizes and utilizes information in unique ways (Mason and Mitroff, 1973). Such personality dispositions are assumed acquired and relatively stable over time (Ausburn and Ausburn, 1978).

The realization that individual differences in personality or cognitive style interact with environmental variables to produce overt behaviors is not new. But recently, the importance of such interactions have been discovered by designers of information systems and decision aids and have imbued the area with new significance one can no longer neglect: the individual differences in human decisionmaking behavior.

The literature relating cognitive style and decisionmaking, though limited in scope and verification, has generally affirmed categorization of distinct cognitive types and correlated modes of decisionmaking. The relative lack of research in this area, however, should not preclude the integration of cognitive style precepts into decisionmaking training, especially as it could be done easily and at small cost. A look, therefore, should be taken at different cognitive types and consideration given to their attitudes toward methods of decisionmaking.

Utilizing a basic "single dimension" model cognitive psychologists have categorized two general modes of problem solving. The first is a detailed problem solving approach and refers to an "analytic" or "field independent" individual. The second is an intuitive, holistic approach and refers to a "heuristic" individual (Huysman, 1970; Witkin, 1967). Other researchers have taken the basic analytic/intuitive dichotomy and fine tuned it. For example, Driver and Mock (1975) constructed a multiple-dimension model emphasizing cognitive complexity, a concept close to the analytic/heuristic (intuitive) approach. These researchers identified four styles along the line of an information-processing component, i.e., how much information is used by the different styles. A similar approach has been taken by McKeeney and Keen

(1974) and Mason and Mistroff (1973). Consistently, some kind of analytic/heuristic dichotomy surfaces as an important descriptor of decisionmaking behavior.

Among researchers exploring the specific relationships between the analytic and heuristic styles and decisionmaker behavior, McKenney and Keen (1974) found distinctive strengths in the different approaches. They report that 75 percent of the business students in the study used their dominant style exclusively. Mistroff and Kilmann (1975) discovered a universal application of the preferred style of decisionmaking in most subjects. In another study Huysman (1970) observed a "personality clash" between individuals of different cognitive styles when working on the implementation of research proposals. Such an effect can lead to decisions based more on style of presentation than information per se and is an important consideration in refining sound decisionmaking qualities. These findings suggest that cognitive decisionmaking attributes such as analytic/heuristic should not be ignored in the study of decisionmaking.

Chorba and New (1980) found that decisionmakers able to request just the information they wanted "tend to progress faster in identifying a successful performance strategy than those that receive an externally prescribed report... (and) the amount and type of data chosen follow a stable pattern over time." The influence of cognitive style on such behavior patterns deserves study: are certain decisionmaking styles better equipped for such an approach? Should information be presented differently to different decisionmaking styles to maximize their unique information-gathering abilities?

Henderson and Nutt (1980) found not only did decision style have "considerable influence on the decisionmaking process," but that the "perception of risk" was influenced by psychological makeup. They also determined that the environmental setting played an important role in conjunction with decision style.

What follows is a description of several cognitive style measures and their purported relationship to decisionmaking. This sample is not meant to be an exhaustive or representative sample of cognitive styles. Rather, selection was made on the basis of the existence of a reliable assessment instrument, high usage as reported in the literature, and apparent relationship to some aspect of decisionmaking.

1.3 COGNITIVE STYLE MEASURES

1.3.1 Reflectivity/Impulsivity

This cognitive style is most often defined in terms of the rate at which alternatives are considered in time and the speed with which responses were made (Ausburn and Ausburn, 1978). When faced with simultaneous response alternatives, individuals who are more reflective than impulsive tend to engage in careful deliberation so that selected choices have a high certainty of being correct. Those individuals more impulsive than reflective tend to respond quickly in choice situations and suffer a high risk of being incorrect.

In the C^3 context, the difference between decisionmakers who are reflective as opposed to impulsive is the time required to make and implement decisions. In the main, reflective decisionmakers will spend more time deliberating a decision than impulsive decisionmakers. Moreover, impulsive decisionmakers by dent of their more rapid responding may select alternatives with a higher risk of being incorrect.

1.3.2 Field Independence/Field Dependence

A tendency for parts of the visual field to be experienced as discrete from the field as a whole is referred to in the perceptual domain as differentiation (Meyer, 1979). To perceive something globally in a relatively undifferentiated manner involves a fusion of the parts of the perceptual field. Individuals exhibiting such a proclivity are called field dependents, while those showing more differentiation are called field independents. Field independents express the tendency to perceive a perceptual field analytically, that is, they demonstrate the ability to experience items as discrete from their background and can overcome embeddedness. In contrast, field-dependent people manifest a more passive and global personality. They have difficulty overcoming embeddedness and concentrating on discrete items composing the global field.

The most often used assessment instruments to measure field dependence are the Embedded Figures Test (Witkin, 1950; Witkin et al., 1971) and the Group Embedded Figures Test (Witkin et al., 1971). Both require the subject to locate a simple form in a more complex background. In the former measure, the time taken for the subject to find the simple form is the basis of the score. In the latter instrument, the score is the number of correctly solved items in a given time. Individuals who find the simple embedded form quickly or who obtain a high number of correct items are labeled field independent, while those who have difficulty finding the hidden form are labeled field dependent. McKenna (1984) has noted that there are over 3000 references to the field dependence literature.

A primary function of any decisionmaker is the collection and collation of information to form a coherent picture of the present situation (i.e., situation assessment). Once such a picture is formulated, decisions are made based on the perceived situation. Decisionmakers who express a more analytical approach to information collection and collation, i.e., field independence, should better differentiate subtle clues embedded in the situation than globally-inclined field dependents. Moreover, the field-dependent decisionmaker should appeal more to doctrine in reaching a decision than a field independent decisionmaker.

1.3.3 Achievement Motivation and Uncertainty Orientation

Achievement motivation and uncertainty orientation are two derivatives from the fields of personality and motivation. Achievement motivation theory states that success-oriented individuals (high in achievement motive - low in fear of failure) prefer and perform better in tasks of intermediate difficulty than failure-threatened individuals (low in achievement motive - high in fear of failure) (Atkinson, 1964; Atkinson and Feather, 1966; Atkinson and Raynor, 1974). A number of rationales have been offered to explain this state of affairs. Explanations falling within a cognitive, information-seeking framework seem most germane. Tasks of intermediate difficulty offer the most information about one's own ability, Weiner (1970,1972) argues. This is because easy or difficult tasks usually result in external attributions to task difficulty or chance while tasks of intermediate difficulty are usually attributed to internal causes, such as ability or effort. Trope (1975) and Trope and Brickman (1975) found that subjects prefer diagnostic tasks, that is, tasks that discriminate well between high versus low ability. Moreover, this was true regardless of task difficulty or subject's achievement motivation, although this preference is stronger for success-oriented than failure-threatened individuals. This has led researchers to believe that success-oriented individuals seem to be more interested than failure-threatened individuals in obtaining information assessing their own ability (Sorrentino, Short, and Raynor, 1984).

Sorrentino et al. (1984) argue, and present supporting results, that the difference in performance (and preference) between success-oriented and failure-threatened individuals occurs primarily in situations that are consistent with one's uncertainty orientation. The performance difference between these two classes of individuals, furthermore, will be greater for uncertainty-oriented than for certainty-oriented individuals. The tying together of achievement motivation and uncertainty orientation is an important development. It helps to better explain performance results in the area, and provides a framework to interpret other cognitive style results that up to now have been difficult to deal with. An example of this latter issue is the risk preference literature.

1.4 THEORIES AND MODELS OF HUMAN DECISIONMAKING AND INFORMATION PROCESSING

1.4.1 Multi-Stage Decisionmaking

Decisionmakers are seldom faced with a single isolated decision. More often the situation demands the decisionmaker to evaluate a number of aspects or hypotheses simultaneously and/or that he make several interdependent decisions. The former situation calls upon the sequential information-processing capability of an individual, while the latter situation is related to an individual's dynamic decisionmaking skills.

Multi-stage decision processes can be classified into two categories, sequential and dynamic. The psychological literature addressing the area of sequential decisionmaking focuses on the topics of sequential statistical interference and optional stopping. The topic of statistical interference is concerned with the diagnostic or information-processing ability of the individual, whereas optional stopping problems combine information processing with simple action selection. The existing literature on dynamic decision-making is primarily concerned with action selection with almost no consideration to the information-processing aspect.

1.4.2 Sequential Probability Inferences

Since most decision tasks involve uncertainty, considerable effort has been expended in studying how people formulate and change their opinions about uncertain hypotheses. Two different approaches are evident in the subjective probability-assessment and revision-of-option literature. One approach, advanced primarily by psychologists and economists, is based on probability theory and statistics and rests on the concept of the rational man. This approach is based on Bayes' rule, which provides a normative representation of how a decisionmaker should revise his probability estimates on the basis of new information. Adjustments to the functional form of the normative model have been the primary method used to deal with descriptive considerations.

Work centering on the Bayesian approach has led to the study of conservatism - a suboptimal human behavior - that produces posterior probabilities nearer to the prior probabilities that would be specified by Bayes' rule (Edwards and Phillips, 1964; Peterson and Beach, 1967). It has been mainly psychologists who have suggested another direction. They argue that individuals are selective, sequential information processors with limited capacity (Hogarth, 1975). This limited information-processing capacity promotes individuals to apply simple heuristics and cognitive strategies that reduce the complex task of predicting values and assessing probabilities to simpler judgmental operations. Tversky and Kahneman (1971, 1973, 1974) have been responsible for much of the work on judgmental heuristics (or bias). Their work demonstates that three judgmental biasing heuristics (representativeness, availability, and adjustment and an. :oring) determine probabilistic inferences in many tasks. These findings, however, can only be described in qualitative terms and, as yet, no quantitative-descriptive theory based on the biasing heuristics has emerged (Pattipati and Kleinman, 1979).

Much of the impetus for the research on normative-descriptive modeling of judgmental processes has been provided by Bayes' rule. A basic hypothesis is that opinions or judgments are expressed in terms of subjective probabilities and that the optimal revision of such judgements is accomplished using Bayes' rule. A large number of studies, involving mainly binominal and multinominal tasks, have examined how subjects make initial probability estimates and then revised them in the light of new information (Edwards and Phillips, 1964; Peterson and Beach, 1967; Donnel and DuCharme, 1975). Generally, results show that the posterior probabilities estimated by subjects were nearer to the prior probabilities than those obtained using Bayes' rule. This phenomenon is referred to as conservatism, and several explanations for it have been advanced. It is believed that conservatism is due mainly to the subject's misinterpretation of the underlying sampling distributions, misaggregation of the data, or simply response bias. Research of Peterson, DuCharme, and Edwards (1968); Wheeler and Beach (1968); and Lichtenstein and Feeney (1968) argues that misinterpretation is generally attributed to the mismatch between subjective and actual (objective) probability distributions. Vlek and Van der Hajden (1967) add to this the tendency for individuals to discount the importance of rare events when they occur. Misaggregation has been advanced as the major source of conservatism primarily by Edwards (1968); Edwards, Phillips, Hayes, and Goodman (1968) refer to the nonoptimal sequential revision of subjective probabilities. Peterson (1968) has advanced the hypothesis of response bias that is related to subjects' unwillingness to use extreme numbers and probabilities. A comprehensive review of the issue of conservatism is provided by Slovic and Lichtenstein (1971), Rapaport and Wallsten (1972), and Slovic, Fischhoff, and Lichtenstein (1977).

In attempts to overcome the shortcomings of a Bayesian model to predict human probability estimates, several empirical modifications have been put forth. These modifications are intended to be embedded into a generalized version of Bayes' rule. Some examples are:

1. Disability or learning impediment function, which takes into account the suboptimal nature of individuals' information-processing system (Ladd, 1978).

2. Impediment ratio function and a factor called the accuracy ratio - found to depend on various task parameters and individual objects thereby disallowing its prediction (Edwards and Phillips, 1964).

3. Constant impediment ratio function, which can represent conditions where subjects do not change their opinions easily (inertia effect) or subjects revise their opinion with every new piece of data (timid learner) (Snapper and Fryback, 1971).

Bayesian revision of opinion is, however, most useful when interwoven with decisionmaking and action selection (Pattipati and Kleinman, 1979). These authors further point out that the posterior probabilities of various hypotheses can be used, in combination with information about payoffs associated with various decisions and states of nature, to maximize the (subjective) expected value, the (subjective) expected utility, or other criterion of optimality. This approach is exemplified in modeling individuals' performance in signal-detection tasks; where the subject must decide whether or not a signal is present in a block of observations.

Experimental results show that people's performances are monotonically related to those predicted by the model. Moreover, it is possible to manipulate subjective decision thresholds by varying prior probabilities and payoff. The amount of change, however, has been found to be less than optimal. Subjects also seem to have difficulty aggregating information across a sequence of trials (Swets and Green, 1961). This is reminiscent of conservatism in Bayesian revision of opinion.

1.4.3 Human Information-Processing Characteristics

A large number of contemporary studies in cognitive psychology have uncovered various heuristics and biases (i.e., deficiencies) that single decisionmakers apply in interpreting and aggregating information. (See Slovic, Fischhoff, and Lichtenstein (1977) and Sage and White (1980) for comprehensive reviews). Of these, the judgmental deficiencies of misperception, representativeness, and availability appear to be the most prominent for probability assessment. Conservatism/recency, along with anchoring and adjustment are most prominent for people's revision of opinion.

MISPERCEPTION

This generally refers to the mismatch between subjective and actual probability distributions, misrepresentations of base rate, and the tendency to place greater belief in values closer to the mean (thereby tending to discount the importance of rare events when they occur). Also, subjects tend to place undue initial confidence on estimates obtained from a limted data set ("belief in the law of small numbers"; Tversky and Kahneman, 1971).

REPRESENTATIVENESS

This heuristic, as advanced by Tversky and Kahneman (1975), refers to individuals' inclination to evaluate the probability of an event on the basis of the degree of similarity between the event and the evidence they have examined to date. If the degree of similarity is high, then the probability of the event is judged to be high.

AVAILABILITY

This heuristic pertains to the finding that people evaluate the probabilities of an event on the basis of the ease with which instances or occurrences involving such events can be recalled or imagined. Availability is considered a valid cue for the assessment of probability because, in general, instances of more frequent events are recalled more easily than those of less frequent events. In a closely related heuristic, the base rate heuristic, decision-makers evaluate the likelihood of two events by comparing the number of times the two events occur and ignore the background rate of occurrence of each event taken separately (Sage, 1981; Bar-Hillel, 1980).

CONSERVATISM AND RECENCY

Conservatism, as advanced primarily by Edwards (1968) and his associates refers to the nonoptimal sequential revision of subjective probabilities; whereby new information is not given as much credibility as Bayesian decision theory would predict. That is, the posterior probabilities estimated by individuals are generally (but by no means universally) nearer to the prior probabilities than those obtained applying Bayes' rule. Recency refers to people's tendency to put <u>more</u> credibility on new information than is estimated by normative theory.

ANCHORING AND ADJUSTMENT

With this heuristic, an initial value or anchor is used as a first approximation to the judgment (Sage, 1981). The initial value is then adjusted according to the information provided. Typically, these adjustments are imperfect and insufficient. Specifically, people tend to overestimate the probability of conjunctive events and underestimate the probability of disjunctive events. To some extent, anchoring and adjustment provides a heuristic adjunct to the concept of conservatism/recency.

Several attempts have been made to capture various heuristics and biases discussed above in quantitative models. For example, recency/primacy effects were incorporated into a model of an antisubmarine warfare commander by manipulating measurement and process noise inputs to the model's Kalman filtering routines (Entin et al., 1984; Alexandridis et al., 1984). A form of anchoring and adjustment was captured in a sequential Bayesian model of subject's attack probability estimates at a task where they were required to discriminate whether missiles were on an attack or test trajectory (Entin et al., 1986). In general, modeling of the subject's heuristics and biases can be accomplished by modifying the objective probability distributions as perceived by the subject or by use of a modified Bayes' rule or Kalman filtering techniques.

1.5 REVIEW OF THE INITIAL ROC EXPERIMENT: COGNITIVE STYLE AND DISCRIMINATION ABILITY

The initial ROC experiment provided the basis for the experiment to be described in the next section, however, only a brief description of the initial ROC experiment methodology and results will be presented. Those who are interested in a more detailed presentation are directed to Entin and Gutowski (1985). For this paper and pencil simulation experiment, the subjects taking the role of a missile warning officer were required to discriminate between real and false missile launches and whether the missile was on an attack or test trajectory. In making this discrimination, the subjects must integrate imperfect heat sensor and x-y position data presented on an overhead projection map of the area, determine if a missile is involved and, if so, whether it appears to be on an attack or test trajectory. The initial information is updated two additional times for a total of three report updates per event (or trial).

A major goal of the initial ROC experiment was to observe if subjects differing in cognitive style would differ in their ability to make discriminations. To assess the subjects' ability to make discriminations in these situations, the experiment was studied as a signal detection problem (Green and Swet, 1966). In this case, attacks are the signal and tests or false alarms are noise. For any group of subjects, the discrimination ability can be examined as an ROC curve. In addition to determining whether subjects with different cognitive styles differ in their discrimination ability, the design also provided a means of investigating multiple-stage decisionmaking in uncertain conditions.

1.5.1 Method

SUBJECTS

Twenty-five student volunteers from a local technical college served as subjects.

PROCEDURES

All subjects completed the Group Embedded Figures Test (Witkin et al., 1971) as a measure of analytic versus global (or heuristic) style (Benbasat and Dexter, 1979; Doktor and Hamilton, 1973). Subjects were then read induction material designed to arouse their interest, induce a belief in the importance of the task, and manipulate the various factors of uncertainty in the experimental design. They were told their duties were to monitor heat sensor data and position data of the heat source, telemetered from Us's satellites to determine if the country of Them has launched an attack.

Subjects were told that a missile's heat signature ranged from 3 to 9 on a scale of 1 to 12. Uncertainty was introduced by explaining that the heat sensor data have an error of ±2 scale units and that other sources like explosions, large fires, electrical storms can all return readings very similar to missiles. Moreover, position data also could exhibit an error radius of 10 miles from the true position. Given these elements of uncertainty, it was the subject's job to decide on which of two trajectories, test or attack, a missile was traversing. Each of Them's 10 missile sites was associated with two trajectories. One led into the country of Us (attack trajectory) and one came close to but missed the country of Us (test trajectory). Subjects viewed a map showing the test and attack trajectories for 90 seconds. All judgments of test or attack were made on maps similar to this one except the test and attack trajectories were not drawn in. The heat sensor reading and heat source position (indicated by a black dot on the map) were updated in each of three reports.

Subjects were instructed to integrate all information and then indicate their probability that Them had launched an attack. Probability estimates were made on a 0 to 4 scale. Fifteen seconds were allotted for each rating. Thirty trials of three reports each were conducted. A random half of the trials depicted an attack trajectory. Sensor readings were generated according to a modified random process; essentially, care was taken to see that the sensor intensity was reasonable given a missile or non-missile trial. Unknown to the subjects, all sensor positions were plotted along their designated trajectories with no error.

1.5.2 Results

According to each subjects' score on the Group Embedded Figures Test, the sample was dichotomized into analytics and globals. Figure 1-1 shows the ROC curves plotted for both analytics and globals. Comparison statistics for the two style groups show significant differences for percentage of area under the ROC curve (analytics' mean = 87.8%, globals' mean = 63.3%, $\underline{F} = 9.84$, $\underline{df} = 1,17$, $\underline{p} < .01$) and d' (analytics' mean = 1.53, globals' mean = 0.49, $\underline{F} = 12.33$, $\underline{df} = 1,17$, $\underline{p} < .01$) in favor of the analytic style. These findings clearly suggest that cognitive style differences can have important effects on multiple-stage decisionmaking.

The data of this experiment may also be viewed as indexing recognition memory for the attack and test trajectories from the various launch sites. Moreover, it is possible that a memory component can be accounting for the cognitive style differences, because subjects were required to memorize the attack and test trajectories. Thus, an estimate of memory storage, θ_s, was developed based on the task analysis represented by the tree structure shown in Fig. 1-2. It is assumed that strength of memory traces can be treated as a dichotomous variable. That is, a trace was either sufficiently or insufficiently stored. If a memory trace is sufficiently stored, then a subject will always give the maximum attack probability response of 4 or the minimum response of 1; if it is <u>not</u> sufficiently stored, then a subject's response

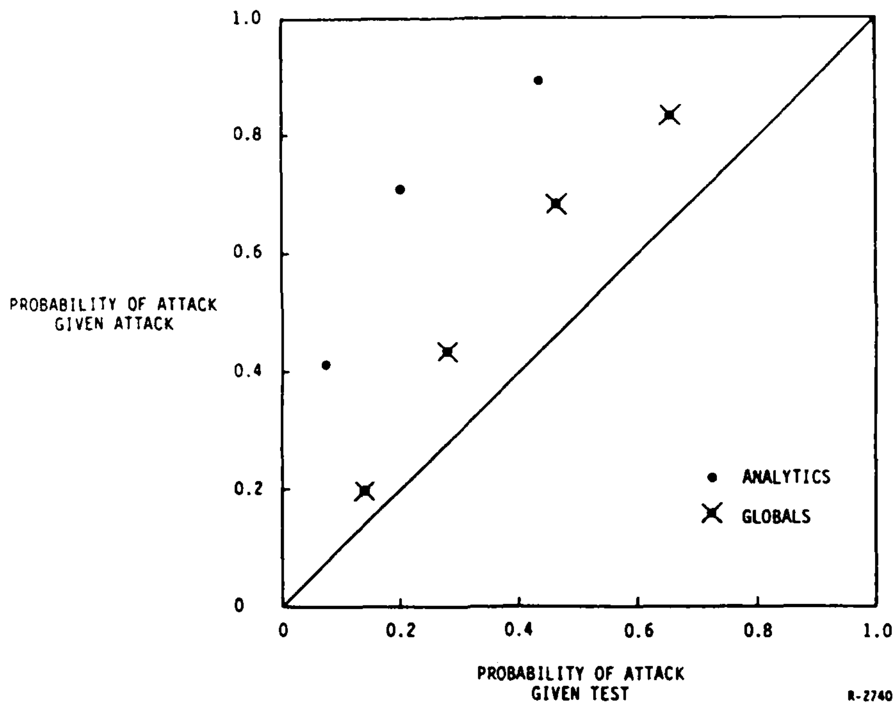

Figure 1-1. Points of the ROC Curve for Analytic and Global Subjects

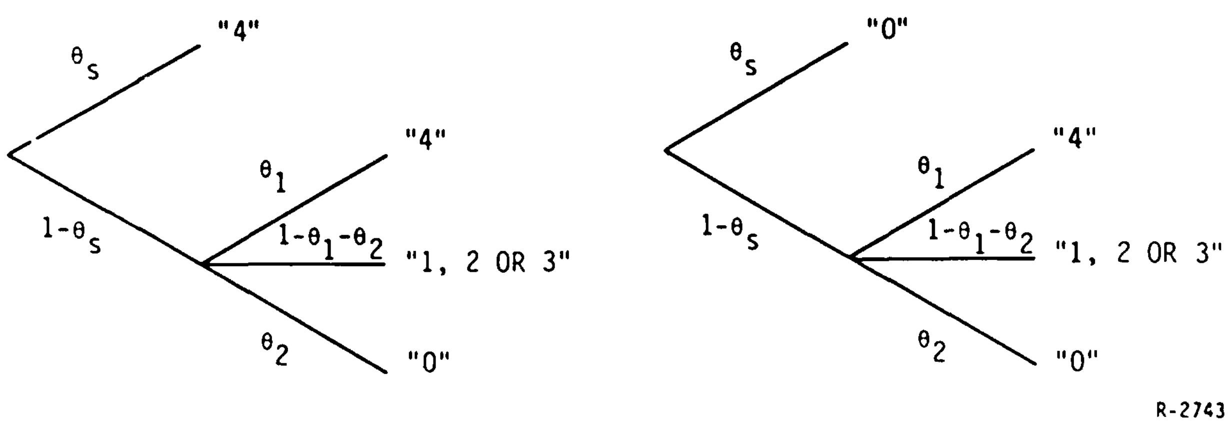

Figure 1-2. Tree Representation of Memory and Rating Parameters to Overt Performance on Attack and Test Trials. Θ_s is the probability of sufficient storage; Θ_1 is the probability of a "4" response conditionalized on insufficient storage; Θ_2 is the probability of a "0" response conditionalized on insufficient storage.

will reflect rating biases and/or guessing. The mean memory storage parameters, Θ_{-S} derived for analytics and globals by report updates are shown in Table 1-1.

TABLE 1-1. MEANS AND STANDARD ERRORS OF THE PARAMETER ESTIMATES

		REPORT		
		1	2	3
ANALYTICS	$\overline{X}$	.10101	.19455	.50655
	σ	.19435	.24127	.27823
GLOBALS	$\overline{X}$	-.01315	.06422	.18701
	σ	.07034	.09890	.30947

An ANOVA of the Θ_{-S} measures shows significant main effects for cognitive style and reports. That is, analytics demonstrated larger Θ_{-S}, than globals ($\underline{F}$ = 5.91, $\underline{df}$ = 1,17, $\underline{p}$ < .03), and Θ_{-S} increased with each additional report update ($\underline{F}$ = 16.34, $\underline{df}$ = 2,34, $\underline{p}$ < .001). The interaction did not, however, reach significance. An *a priori* contrast computed for Reports 1 and 3 (i.e., Report 2 was omitted) by cognitive style did, however, prove significant and are displayed in Fig. 1-3 ($\underline{t}$ = 1.80, $\underline{df}$ = 17, $\underline{p}$ < .05). The results are consistent with previous analyses and demonstrate that the overall recognition performance of analytics is consistently superior to that of globals. The results also indicate that the recognition performance of both groups is enhanced by providing additional memory cues, and that the facilitiation due to cueing is greater for analytic than for global individuals. The results also suggest that memory ability could also be playing a part in the discrimination differences exhibited between analytics and globals.

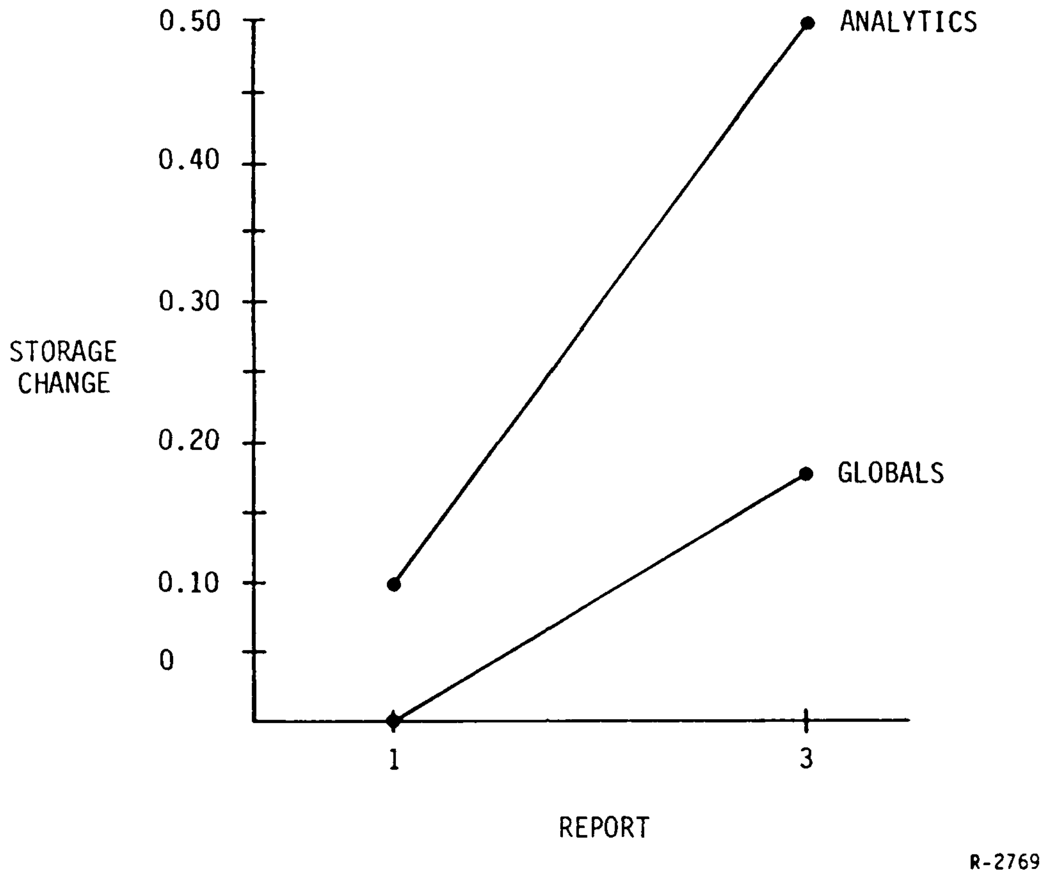

Figure 1-3. Storage Change From Report 1 to Report 3 as a Function of Cognitive Style

1.6 EXPERIMENT TWO: MULTI-STAGE DECISIONMAKING AND COGNITIVE STYLE

Drawing on the literature surveyed and on the initial ROC experiment a research design was devised to investigate multi-stage decisionmaking and cognitive style in conditions of uncertainty. The new research plan extended the prior experimental design by introducing missile site attack probability to investigate how subjects dealt with probabilistic information and to provide prior probabilities for the multi-stage decisionmaking analysis. Heat sensor data were manipulated to provide a source of systematically varied uncertainty and procedures were introduced to allow investigation of the memory hypotheses promulgated in the prior experiment. Also, two additional cognitive style measures were administered to further explore decision style effects. The following sections deal respectively with a description of the methodology used in the second experiment, subsequent results, an attempt to model the multi-stage decisionmaking results, and a discussion of results.

SECTION 2

METHODOLOGY

2.1 SUBJECTS

Twenty male and female volunteers from a local technical college served as subjects.

2.2 ASSESSMENT OF COGNITIVE STYLES

The Group Embedded Figures Test (GEFT) (Witkin et al., 1971), a purported measure of field interdependence, and the first third of the Test Anxiety Questionnaire (TAQ) (Mandler and Sarason. 1952) were administered to all subjects. Both instruments were administered and coded according to the literature pertinent to each. Smith (1964) has pointed out that the first third of the TAQ (12 items and 3 fillers) correlates between .84 and .90 with the total score and can be used in lieu of the whole scale with little loss of reliability. Designers of the GEFT report a split-half Spearman-Brown reliability coefficient of .82 for the scale. The TAQ is ubiquitous throughout the psychological research literature as a reliable and valid measure of anxiety (cf. Atkinson and Feather, 1966; Raynor and Entin, 1982). According to the scores on the GEFT, each subject was classified as either exhibiting an analytic or global (sometimes referred to in the literature as heuristic) style (Benbasat and Dexter, 1979; Doktor and Hamilton, 1973). Individuals scoring above the median on the TAQ were assumed to manifest a high anxious style while those below the median were considered low anxious.

A third style measure, newly developed by Gutowski and Entin (1985), assessed risk taking. The instrument is based on work by Gutowski (1984) and presents the subjects with 18 pairs of alternatives or options. For each pair of options, the subjects were asked to indicate which they preferred. Each option described four pieces of information: (1) the best possible outcome, (2) the probability that the best outcome will occur, (3) the worst possible outcome, and (4) the probability that the worst outcome will occur. Figure 2-1 presents the instructions and several example option pairs. Unknown to the subjects, the expected-value of each half of an option pair was equivalent. The option describing the most negative or worst outcome (which in most cases also defined the more negative expectancy-value outcome) was defined as the more risky. To arrive at a score, subjects received one point for each risky option preferred. The sum over the 18 items was a subject's risk-taking score. It was assumed that individuals above the median on the risk-taking scale would exhibit a relatively higher risk-taking decision style than those below the median. An independent reliability study based on 57 subjects revealed a reliability coefficient of .56 for the 18 item version and a coefficient of .76 ($N = 33$) for a 54 item version. It was concluded that the risk-taking measure showed reasonable reliability.

2.3 STIMULUS MATERIALS

The materials used in this experiment were an extension and elaboration of those employed in the initial experiment. Once again, a map display is used to delineate the geographic areas of two hypothetical countries now referred to as Illia and Thanos. The overhead map projection of the two countries is similar to that used before with some notable exceptions. As

NAME ______________________________ DATE ______________

In the following decisionmaking task, you will be presented with pairs of alternatives or options. For each pair of options, you should carefully consider each option and decide which you prefer. You should indicate your preference by entering the number (1 or 2) of your preferred option in the right column of the response sheet.

The description of each option ordinarily involves four pieces of information: (1) the best possible outcome, (2) the probability that the best outcome will occur, (3) the worst possible outcome and (4) the probability that the worst outcome will occur. For example, the option described in the first four columns on the first line below offers a 2/3 chance to gain $20 and a 1/3 chance to lose $10. The option described in the next four columns of that line offers a 1/6 chance to gain $85 and a 5/6 chance to lose $5. Thus, most options involve uncertainty since one cannot be sure which of the two outcomes will occur. Some of the options, however, are described by only two pieces of information. These options involve no uncertainty since only one outcome is possible (i.e., the probability of that outcome occurring is exactly 1.0). For example, the option described on the second line below guarantees a gain of $12. The second option on that line describes an option which offers a 1/3 chance to gain $40 and a 2/3 chance of not gaining or losing.

To summarize, you should consider the possible outcomes and the respective probabilities of each option and then indicate which of the options you prefer. In some cases, you may find both options unattractive. In those cases, you should indicate that you prefer the option which you find less unattractive.

OPTION 1					OPTION 2					
BEST OUTCOME	PROBABILITY OF BEST OUTCOME	WORST OUTCOME	PROBABILITY OF WORST OUTCOME		BEST OUTCOME	PROBABILITY OF BEST OUTCOME	WORST OUTCOME	PROBABILITY OF WORST OUTCOME		PREFERENCE
20	2/3	-10	1/3		85	1/6	-5	5/6		
12	1	-	-		40	1/3	0	2/3		
10	5/6	-60	1/6		20	5/6	-110	1/6		
-10	1	-	-		20	2/3	-45	1/3		

Figure 2-1. Risk Preference Scale

(PLEASE DO NOT TURN THE PAGE UNTIL ASKED TO DO SO) depicted in Fig. 2-2, the two trajectories associated with each missile site are now drawn in and clearly visible, making it unnecessary for subjects to memorize them. Moreover, the angle between the test and attack trajectories was manipulated. For a random half of the trajectory pairs, a small angle (6 degrees to 11 degrees) was depicted, while the other half showed a relatively larger angle (21 degrees to 29 degrees). Large and small angles were counterbalanced within strata of other independent factors and geographically across missile launch sites.

The number of missile launch sites in Thanos was increased from 10 to 12 and associated with each site was a probability indicating the likelihood that an attack would be launched from that site. A random half of the probabilities indicated a low chance of attack (0.15 to 0.25) while the other half indicated a relatively higher chance of attack (0.45 to 0.60). High and low probability sites were counterbalanced within the strata of other independent variables and geographic location.

2.4 PROCEDURE

Subjects followed along as the following induction materials were read aloud.

> A drawn-out low-level war is occurring between Illia and Thanos, similar to that between Iran and Iraq or Israel and its Arab neighbors. At times, the two countries have exchanged conventionally armed missiles, artillery barrages, and even attempted invasions. As a consequence, Illia has Thanos under constant surveillance and Thanos does the same.
>
> You are a missile surveillance officer (MSO) for Illia. As such, your duty is to monitor heat sensor data and position data of the heat source, telemetered from the satellites, to determine if a missile attack is underway or not. This is a very important decision. If you say there is an attack when there is none, you may start a needless and costly exchange of retaliatory hostilities. On the

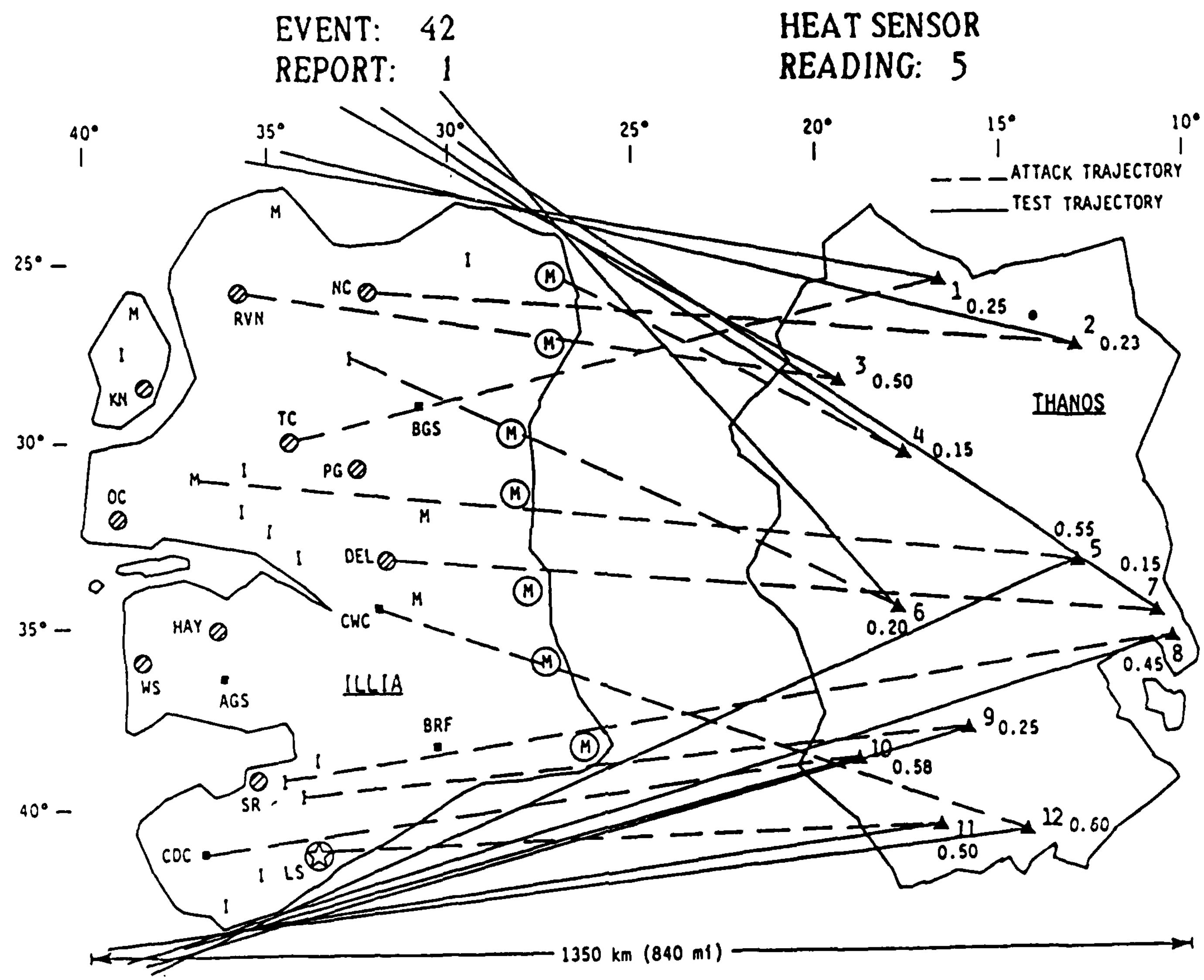

Figure 2-2. Example of Overhead Map Projection Used in Experiment

other hand, if you decide there is not an attack when there really are missiles coming, you inhibit your own antimissile defenses and give Thanos a costly first strike edge.

In making your decision, you must keep several things clearly in mind. First, not all heat sources detected by the sensors are missiles and a missile detection does not necessarily mean attack. The heat signatures of all Thanos's missiles range between 5 and 8 on an intensity scale from 1 to 12. The sensors, however, have an error of about plus or minus 2. Explosions, large fires, and electrical storms, moreover, can all return readings in the 5 to 8 range. Alternately, Thanos's electronic deception attempts can sometimes cause even greater error in the heat sensor returns. Such deception attempts can bias true sensor readings in the 5 to 8 range to the extremes (i.e., 1 or 12). Position data is also not without error. This is due to inaccuracies inherent in the tracking radar (and sometimes to Thanos's electronic deception attempts).

It is widely known that Thanos engages in an active missile testing program. Thanos routinely launches test missiles on trajectories that often come close to the borders of Illia. It is surmised that this latter action might also serve as a harassment and as an attempt to goad Illia into launching its counterforces needlessly.

From the many observations of Thanos's attack and test missile trajectories, as well as geographic factors, prevailing winds, weather patterns, distance to important targets, and proximity to open waters, intelligence tells us that each of Thanos's launch sites has one favored attack trajectory and one favored test trajectory. Twelve missile launch sites within Thanos have been identified and monitored. This surveillance has shown that it is more likely for Thanos to launch attack missiles from some sites than others. The probability indicating the likelihood that an attack would be launched from a site is depicted on the map display. Thus, the probability of .50 associated with site number 3 indicates that the Illian intelligence experts feel there is a 50 percent chance that a missile launch from this site will be an attack missile. Alternately, the .20 probability accompanying site number 6 is interpreted to mean Illia's experts feel that there is only a 20 percent chance that a missile launched from this site would be an attack missile and an 80 percent chance that it would be a test missile.

Your task as the MSO is to integrate all the information available, i.e., the heat sensor data, position data, launch site attack missile probability, etc., and decide whether or not a missile has been launched and whether the missile is on a test or attack trajectory. Based on this decision, you then indicate your probability that Thanos has launched an attack. Indicate your probability estimate of attack on a 1 to 9 scale, where 1 means a 1 in 10 or 10 percent chance of attack, 2 means a 2 in 10 or 20 percent chance of attack, 3 means a 3 in 10 or 30 percent chance of attack, ... and 9 means a 9 in 10 chance or 90 percent chance of attack. On a second scale, indicate your certainty in the probability of attack rating you just gave. Make this rating on a 1 to 5 scale where 1 means Very Low cetainty and 5 means Very High certainty in the attack probability.

The area depicted on the map is approximately 840 miles (1350 km) on a side. The conventionally armed cruise-like missiles employed by Thanos have a speed from 600 to 750 mph (945 to 1200 kph). Thus, all targets are within an hour's flight time of any launch site during attack.

During each detection of an event, you will have the opportunity to make three judgments. This is because the satellite surveillance system provides three independent reports of heat intensity and position spaced about 5 minutes apart.

For each event, you will receive a heat intensity reading and be shown a map location where the heat appears to be originating. Remember heat sensors have an error of about plus or minus 2. Thanos's electronic deception can sometimes introduce even greater error, and position tracking might be off by as much as 20 miles (32 km) from the actual position.

Based on this data, and the likelihood the site associated with the heat source might launch an attack missile, you should formulate your probability that an attack is underway and indicate this on the probability of attack scale. You should also rate your certainty or strength of belief in the attack probability you have indicated. You will then receive a second report updating the heat intensity reading and map location of the heat source. A second pair of ratings is made based on all the pertinent information to date. This will be followed by a third updating of the data from which you derive your third pair of ratings. The third report marks the end of that event.

Throughout this reading of the induction instructions, a sample map display, such as that in Fig. 2-2, was projected on a screen behind the _E_. As the different aspects of the display were described, the _E_ pointed these out on the projected map. At this point in the instructions, an example was introduced. The _E_ read aloud the following material as the subject followed along.

Let's run through a sample event. Consider carefully all the information presented in the first report.

1) The apparent location of the heat source can be as much as 20 miles (32 km) off the actual position; however, it can be your best source of information. First associate the heat source location with a missile launch site. This is usually easy. Next, try to associate the heat source location with one of the two trajectories. This may be difficult, but do your best.

2) Heat sensor reading. Error in heat sensor is ±2, although electronic deception can increase the error.

3) Probability that an attack missile would be launched from the site associated with heat source.

Integrate this information and decide if there is a missile, and if so, the probability it is on an attack trajectory. You would then record this estimate on the response sheet, followed by your certainty or belief in the attack probability you just gave.

Here is the second report. Consider its information carefully, particularly the heat source location. You now have two pieces of information: The current location and the past location. Also, remember that a missile will travel about 50 to 60 miles between reports. Try to use all this information. Does the heat source location estimates seem to be "bouncing" around on either side of a trajectory? If so, that's probably the correct trajectory. If not, which do both appear to be nearest? You would then make your second attack probability and certainty estimates.

Here is the third report. Go through the operations one more time. This is the end of the event.

Subjects were asked if they had any questions and then were directed to make their probability and certainty ratings on the forms provided. Map displays, along with the heat sensor readings, were presented via an overhead projector. A heat location was depicted on the map by a black dot. Subjects were given 20 seconds to record each pair of ratings. The slide for Report 1 was then removed and replaced with the slide for Report 2 for that event. The display for Report 2 once again showed the map, but now with an updated heat sensor reading and a second black dot showing the new heat location. After 20 seconds, this slide was replaced with one depicting Report 3. Thus, subjects made a cascading of three probability estimates of attack and three of confidence for each trial (or what is referred to the subjects as an event). Thirty-six events (trials) were conducted. A random half of the events depicted an attack and the other 18 events were nonattack oriented, being either tests or nonmissiles.

Heat sensor reports were systematically manipulated. For a random third of the events, the heat sensor reports were clearly out of the signature range of Thanos's missiles (i.e., 1, 2, 11, 12). In another random third of the trials, the reports were within the ±2 error range of Thanos's missile (i.e., 3, 4, 9, 10). For the remaining third, the heat sensor reports were within the known heat signature range of Thanos's missiles (i.e., 5, 6, 7, 8). When plotting the position of the heat source, an error of from 0 to 20 miles was introduced. To produce this deviation, a random number from -20 to +20 was generated for each report. If the number was positive, the deviation was plotted (approximately) perpendicular from the top or right of the true trajectory, in scale with the magnitude of the error (i.e., the random number generated). If the number was negative, the deviation was plotted perpendicular from the bottom or left of the true trajectory, in scale with the magnitude of the error. Thus, if the number generated was -12, the position of the heat source would be shown with a perpendicular offset of 12 miles from the bottom or left of the true trajectory. Care was taken to insure that the same number of reports had positive as had negative deviations and that the same number of reports had offsets of between 1 and 10 miles as had offsets of between 11 and 20 miles.

2.5 ANALYSIS OF THE DATA

As in the initial experiment, the data were examined first as a signal detection or discrimination experiment. ROC statistics were calculated and analyzed by RSCORE III (Dorfman, 1983), a software package specifically designed to analyze ROC experiments. Attack probability and uncertainty were then organized into a traditional multivariate format and analyzed in an outcome (attack/test) × missile site probability (high/low) × heat signature range (out of range/in error range/in signature range) × reports (first/second/ third) four-way within-subjects' multivariate analysis of variance.

SECTION 3

RESULTS

3.1 ROC ANALYSES

Table 3-1 shows the summary of statistics for the ROC analyses of probability of attack ratings by decision styles. Inspection of this table and Fig. 3-1 reveals a significant difference in favor of subjects exhibiting the analytic style for area under the ROC curve ($\underline{F} = 6.87$, $\underline{df} = 1,18$, $\underline{p} < .02$) and for d' ($\underline{F} = 8.20$, $\underline{df} = 1,18$, $\underline{p} < .01$). Neither of the other two style measures produced significant results. The results reported for the analytic and global styles clearly replicate the style results of the previous experiment where the discrimination ability of analytic subjects proved superior to global subjects. An analysis of certainty (confidence) ratings by decision style, summarized in Table 3-2 and Fig. 3-2, depicts a somewhat different pattern. Overall, subjects' certainty did not differ much in attack and test situations. This is exemplified by the small departure from the chance line and the relatively small d' values. It should also be noted that the ROC curve for all style groups is negative (i.e., negative d's and percentages of area under the ROC curve of less than 50). Moreover, analytics did not differ significantly from globals, nor did high anxious subjects differ from low anxious subjects in the ROC analysis of certainty. Only risk-taking style produced a significant difference (see Table 3-2). Subjects exhibiting a high risk-taking style tended to demonstrate a more negative ROC curve; that is,

TABLE 3-1. SUMMARY STATISTICS FOR ROC ANALYSIS OF PROBABILITY OF ATTACK RATINGS BY DECISION STYLES

MEASURE	ANALYTIC	GLOBAL	ANXIETY HIGH	ANXIETY LOW	RISK HIGH	RISK LOW
d'	1.31	0.83*	1.06	1.03	1.13	0.96
AREA UNDER ROC CURVE	81.93	71.36*	76.64	75.59	78.22	74.02

*Differences significant at $p < .02$ level.

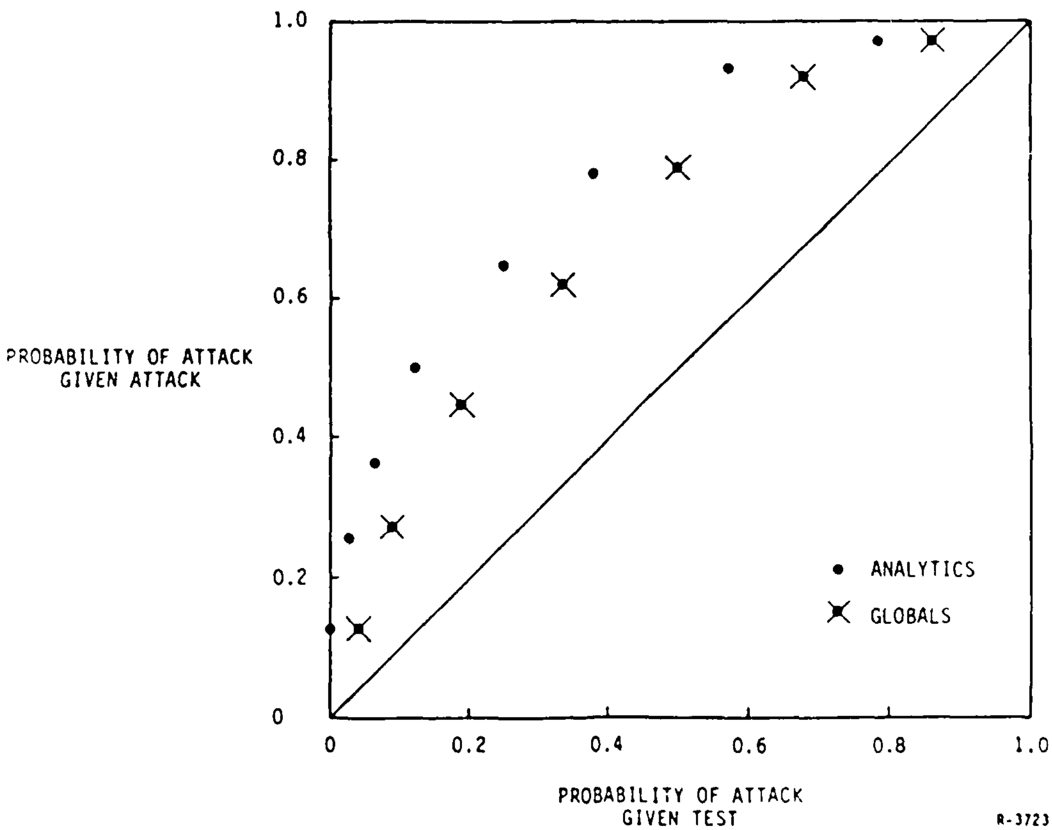

Figure 3-1. ROC Curve Points for Analytic and Global Subjects

TABLE 3-2. SUMMARY STATISTICS FOR ROC ANALYSIS OF PROBABILITY OF CERTAINTY RATINGS BY DECISION STYLES

MEASURE	ANALYTIC	GLOBAL	ANXIETY HIGH	ANXIETY LOW	RISK HIGH	RISK LOW
d'	-0.19	-0.20	-0.28	-0.12	-0.29	-0.10
AREA UNDER ROC CURVE	38.98	44.35	42.38	41.49	36.63	47.24*

*Differences significant at $p < .05$ level.

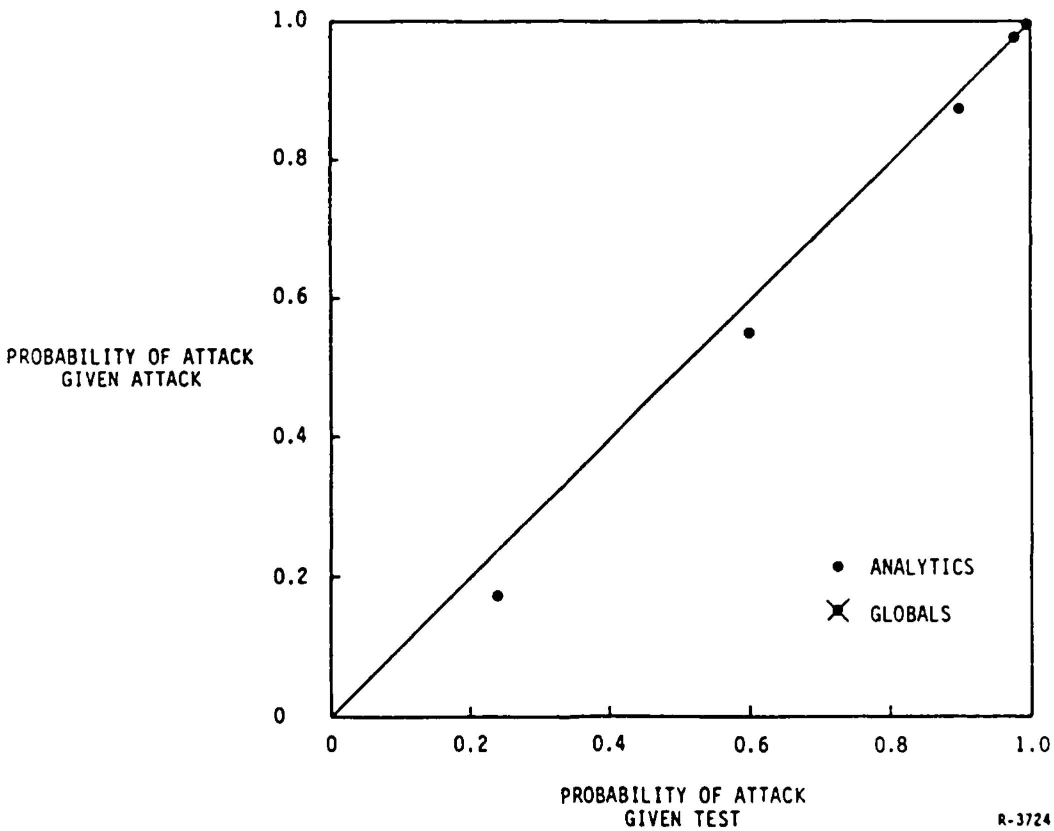

Figure 3-2. ROC Curve Points for all Subjects on the Certainty Ratings

reportedly they were more certain in their probability of attack ratings during false alarms and less certain during attacks than subjects exhibiting a low risk-taking style ($F = 4.39$, $df = 1,18$, $p < .05$).

Table 3-3 shows the summary of two regression analyses where group field independent-dependent (GFID), test anxiety, and risk-taking scores, along with their interactions, were used first to predict area under the ROC curve and d' for attack probability and then to predict area under the ROC curve and d' for certainty. Only GFID score proved predictive of d' and area under the ROC curve for attack probability. However, the correlations were moderate and only a bit more than 20 percent of the variance is accounted for indicating only weak predictive power for GFID score. A similar analysis for the certainty estimates revealed that a linear combination of GFID, test anxiety, and their interaction could account for 57 percent of the variance related to area under the ROC curve. None of the style variables or their interactions were predictive of d' for the certainty ratings.

3.2 ANALYSES OF MANIPULATED INDEPENDENT VARIABLES

To examine the manipulations of the various independent variables on multi-stage decisionmaking, the attack probability ratings were analyzed in an outcome (attack/test) × missile site probability (high/low) × heat signature range (out of range/in-error range/in-missile range) × reports (first/second/third) four-way within-subjects multivariate analysis of variance (MANOVA). Table 3-4 shows the means for the four main effects. As can be seen, subjects reported significantly higher attack probability ratings in attack than test situations ($F = 70.96$, $df = 1,19$, $p < .001$). This finding parallels the ROC analysis results showing that subjects can reliably discriminate between attack and test (false alarm) situations. Subjects also reported significantly

TABLE 3-3. SUMMARY OF STEPWISE MULTIPLE REGRESSION ANALYSIS

DEPENDENT VARIABLE	INDEPENDENT VARIABLE PREDICTORS	MULTIPLE r	PERCENT VARIANCE ACCOUNTED FOR
	ATTACK PROBABILITY		
d'	GFID	0.48	23%
Area Under the ROC Curve	GFID	0.46	21%
	CERTAINTY RATINGS		
d'	-		
Area Under the Roc Curve	GFID, TAQ, GIFD × TAQ	0.75	57%

TABLE 3-4. PROBABILITY OF ATTACK AS A FUNCTION OF THE FOUR INDEPENDENT FACTORS

VARIABLE	LEVEL	MEANS	OUTCOME
OUTCOME	ATTACK TEST	5.46 3.51	F = 70.96, df = 1,19, p < .001
SITE PROBABILITY	HIGH LOW	4.91 4.06	F = 49.97, df = 1,19, p < .001
HEAT SIGNATURE RANGE	IN ERROR OUT	4.71 4.50 4.25	F = 7.18, df = 2,38, p < .002
REPORTS	FIRST SECOND THIRD	4.21 4.58 4.66	F = 19.53, df = 2,38, p < .001

higher attack probabilities when the purported missile was associated with a high probability of attack site than a low probability of attack site (F = 49.97, df = 1,19, p < .001). Obviously, subjects are biased by the prior probabilities attached to the various missile launch sites. Further inspection of Table 3-4 shows that subjects' attack probability ratings are also significantly biased by heat signature range (F = 7.18, df = 2,38, p < .002).

Attack probability ratings increase as the reported heat sensor reading nears in-missile range. Attack probability significantly increases with each new report update ($F = 19.53$, $df = 2,38$, $p < .001$). The outcome × reports interaction shows more specifically what is occurring for the probability ratings, thus further discussion of this effect will be delayed until the interaction is discussed.

The means for all the two-way interactions are reported in Tables 3-5a through 3-5f. From the outcome × missile site probability means in Table 3-5a, we see that subjects had an easier time discriminating between test and attack conditions when site probability was low than high ($F = 7.12$, $df = 1,19$, $p < .02$). The outcome × heat signature interaction reported in Table 3-5b shows that subjects can discriminate better between attack and test conditions when the sensor report was clearly out of range or within the error range, than when the sensor report was in-missile range ($F = 8.77$, $df = 2,38$, $p < .001$). Results of the outcome × reports interaction in Table 3-5c show that subjects discriminate better between test and attack conditions as a benefit of each new report update ($F = 85.78$, $df = 2,38$, $p < .001$). It can also be seen that the increase in attack probability occurring in the attack condition is greater than the decrease in attack probability occurring in the test condition, thus the net effect is a seeming increase in attack probability with each report update. It is precisely for this reason that the main effect for reports showed an increment of attack probability with each report update. The missile site probability × heat signature interaction reported in Table 3-5d shows that heat sensor information has little effect on attack probability when the attack likelihood of a missile site is high, but when the attack likelihood of a site is low, attack probability ratings

TABLE 3-5. TWO-WAY INTERACTIONS FOR ATTACK PROBABILITY

a) OUTCOME × SITE PROB.
$F = 7.12$, $df = 1,19$, $p < .02$

OUTCOME	SITE PROB	
	LOW	HIGH
ATTACK	5.13	5.80
TEST	2.99	4.02

b) OUTCOME × HEAT SIGN.
$F = 8.77$, $df = 2,38$, $p < .001$

OUTCOME	HEAT SIGN. RANGE		
	OUT	ERROR	IN
ATTACK	5.28	5.63	5.48
TEST	3.22	3.37	3.94

c) OUTCOME × REPORTS
$F = 85.78$, $df = 2,38$, $p < .001$

OUTCOME	REPORTS		
	FIRST	SECOND	THIRD
ATTACK	4.33	5.44	6.62
TEST	4.10	3.72	2.71

d) SITE PROB. × HEAT SIGN.
$F = 15.30$, $df = 2,38$, $p < .001$

SITE PROB.	HEAT SIGN. RANGE		
	OUT	ERROR	IN
HIGH	4.99	4.75	5.00
LOW	3.52	4.24	4.42

e) SITE PROB. × REPORTS
$F = 9.71$, $df = 2,38$, $p < .001$

SITE PROB.	REPORTS		
	FIRST	SECOND	THIRD
HIGH	4.86	4.90	4.98
LOW	3.57	4.27	4.35

f) HEAT SIGN. × REPORTS
$F = 11.65$, $df = 4,76$, $p < .001$

HEAT SIGN.	REPORTS		
	FIRST	SECOND	THIRD
IN	4.42	5.02	4.70
ERROR	4.07	4.53	4.89
OUT	4.15	4.20	4.41

increase as the heat signature approaches in-missile range ($F = 15.30$, $df = 2,38$, $p < .001$). Table 3-5e shows that the additional information provided with each report update has little impact on attack probability ratings when the attack likelihood of a missile site was high. However, when the attack likelihood of a missile site was low, the second report update increased attack probability considerably ($F = 9.71$, $df = 2,38$, $p < .001$). The heat signature × reports interaction presented in Table 3-5f and Fig. 3-3 shows that, initially, heat sensor returns in the in-missile range produce higher probability of attack ratings than either out of range or in the error range. During the second report update, heat sensor information produces an out of range, in-error range, in-missile range ranking of ascending attack probabilities, while during the third report, a reading of the heat sensor in the in-missile range causes the probability of attack ratings to fall between the error and out of range readings ($F = 11.65$, $df = 4,76$, $p < .001$). Overall, subjects tend to give higher attack probabilities as the heat sensor reading approaches in-missile range. This effect is strongest in the second report and weakest in the third report.

The ANOVA also revealed that two of the four three-way interactions were significant. Figure 3-4 shows the significant ($F = 5.59$, $df = 4,76$. $p < .001$) outcome × heat signature × reports interaction graphically, and it is obvious that outcome and heat signature interact differently at each level of the reports factor. Initially, subjects showed the same weak ability to discriminate between attack and test condition when the heat sensor reading was out of range and within the error range. A return of in-missile range left subjects unable to discriminate. Moreover, the attack graph was nearly flat across the three heat signature ranges while the test graph shows a slight upturn between error range and in-missile range. After the second report update, subjects demonstrate a good, and about equal, ability to discriminate between attack and test when the heat sensor returns were out of range and in-error range. Subjects' discrimination ability decreases somewhat when an in-missile reading was returned. Both the attack and test graphs demonstrate a small positive gradient across the heat signature levels; however, the test graphs becomes steeper between the in-error and in-missile ranges. By Report 3, the subjects' ability to discriminate was improved further when the heat sensor reading was out of range and showed further improvement when the heat sensor reading was in-error range. In comparison, the subjects' discrimination ability has not improved as much when readings of the heat sensor were in-missile range. Note, the test graph shows a small positive increase across the heat signature levels while attack shows more of an inverted U.

Figure 3-5 shows the significant outcome × site probability × reports interaction ($\underline{F}$ = 5.15, $\underline{df}$ = 2.38, $\underline{p}$ < .01). At the start, subjects demonstrate little ability to discriminate attack from test condition, regardless of the site probability level. However, both attack and test show a positive slope, as attack probabilities are higher when the attack likelihood of a missile site is high. After the second report, the picture changes. Subjects appear able to make good discrimination when site probability is high. This difference in discrimination ability is due solely to the upward slope of the test graph, as the attack line is flat. With Report 3, subjects exhibit very good discrimination ability between attack and test conditions and this ability is better when missile site probability is low than high. The primary reason for this is, once again, the test graph demonstrates a steeper upward slope than the attack graph.

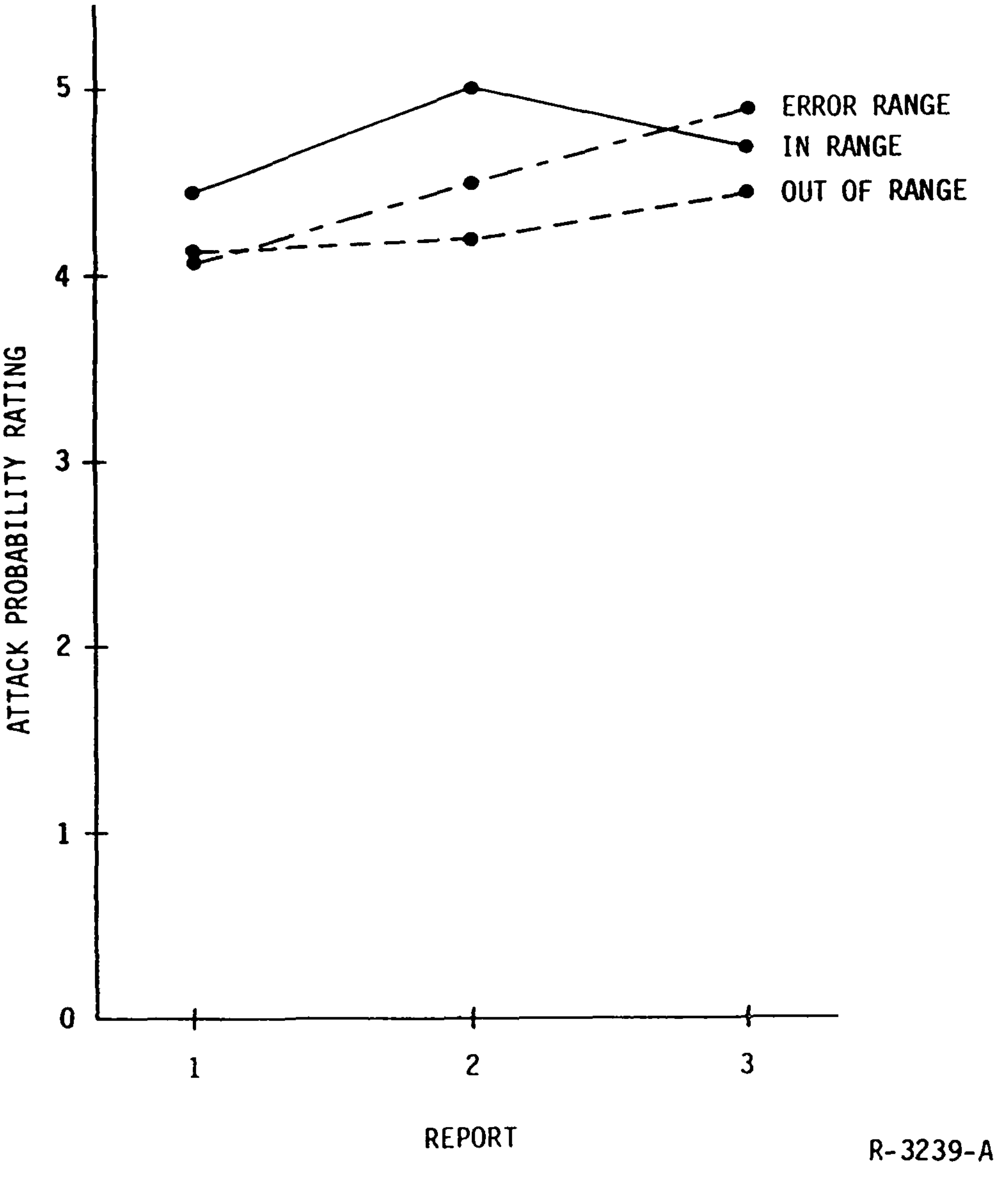

Figure 3-3. Attack Probability as a Function of Heat Signature and Reports

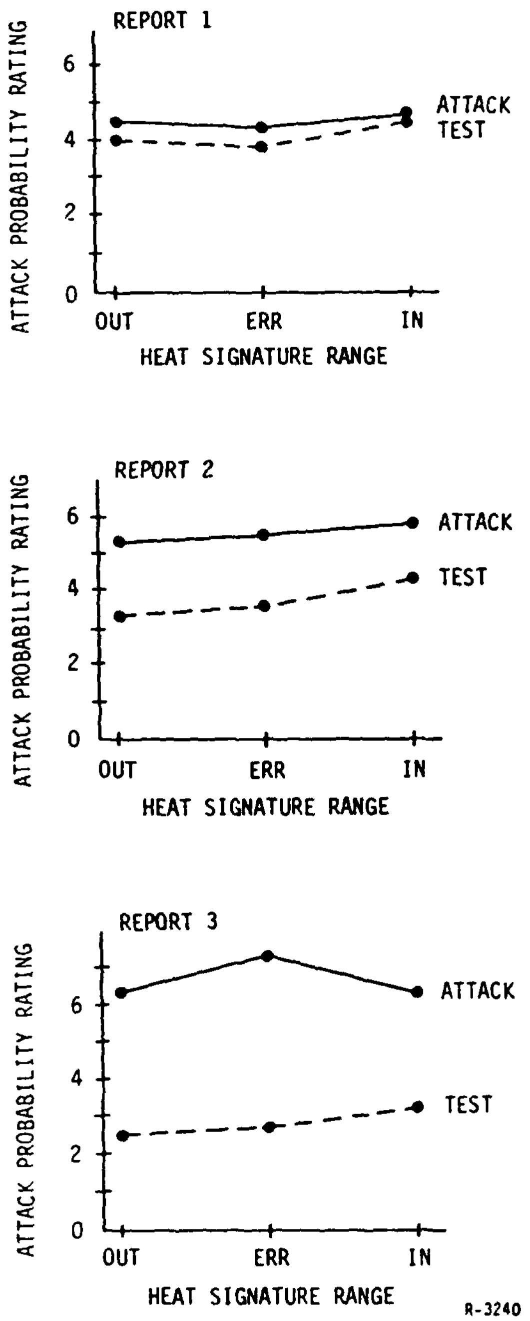

Figure 3-4. 3-Way Interactions (Outcome × Heat Sign. × Reports)

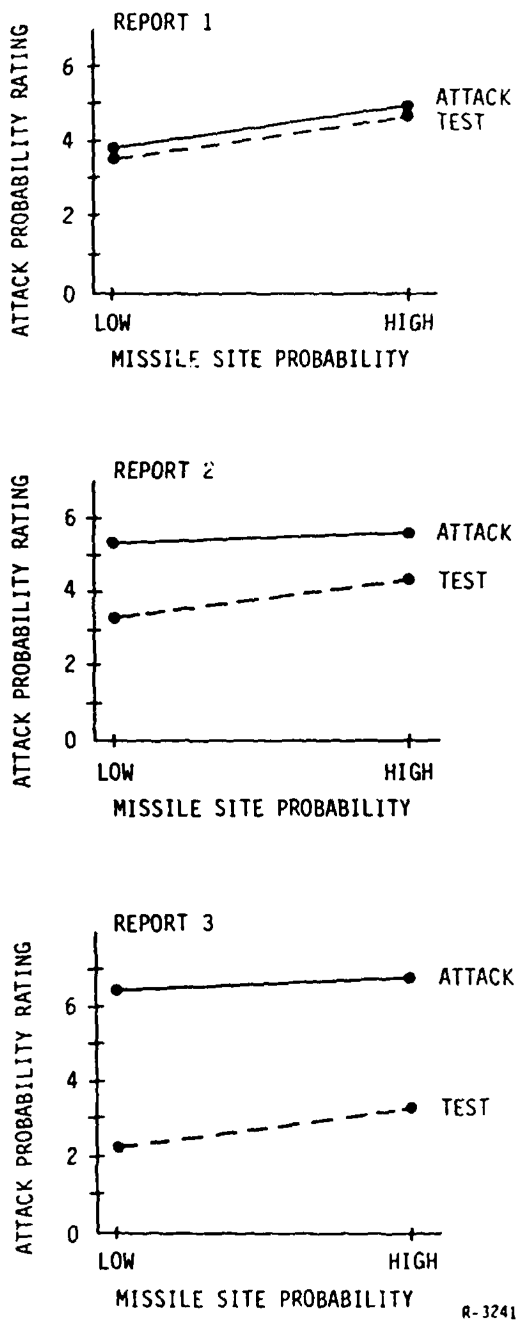

Figure 3-5. 3-Way Interactions (Outcome × Site Prob. × Reports)

3.3 REGRESSION ANALYSES

A stepwise multiple regression analysis was performed to predict attack probability ratings from the three style measures and the preceding attack probability rating. To prepare for this analysis the attack probability ratings were averaged over conditions, such that, for each subject, a mean attack probability rating was obtained for Report 1, a mean attack probability rating was obtained for Report 2, and a mean attack probability ratings was obtained for Report 3.

For the first report, only the style measures (i.e., analytic versus global style, anxiousness, and risk taking) and their four interaction terms were available to predict the initial attack probability rating. The regression analysis identified only one style measure, risk taking, to be predictive of the initial attack probability rating, albeit very weakly. Risk taking correlated .30 with attack probability and accounts for 9 percent of the variance. Inspection of the residuals showed that no other style measure or interaction term was even remotely close to being predictive.

The variables available to predict the attack probability rating at Report 2 included the three style measures and their four interaction terms with the addition of the attack probability rating given at Report 1. Not surprisingly, the regression analysis revealed that the probability rating given for Report 1 is the best predictor of the attack probability for Report 2. Report 1's rating correlates .89 with Report 2's rating, thus accounting for 79 percent of the total variance. Only one other variable was able to significantly enhance this relationship; GFID. With the addition of GFID, the multiple correlation increases to .92 and the variance accounted for increases to 85 percent.

The last regression analysis used the attack probabilities given for Reports 1 and 2, coupled with the three style measures and their four interaction terms to predict the attack probability given for Report 3. The attack probability previously given in Report 2 proved most predictive of the attack probability for Report 3. Report 2's rating correlated .89 with the probability rating in Report 3 and accounted for 79 percent of the total variance. None of the remaining variables were signficantly related.

SECTION 4

A MODEL FOR SEQUENTIAL INFERENCE

In addition to the statistical analyses of the data, a modeling effort was undertaken to analytically study the sequential inference behavior exhibited by the subjects. The modeling approach follows from principles described by Rapoport (1975) and is referred to as normative-descriptive. To begin, a normative model is developed, which in this case is a purely sequential Bayesian scheme, to optimally determine the attack probabilities. The normative model makes these determinations based on inputs derived from the decision environment (i.e., missile site probability, heat signature, position of heat source, etc.). Following the formal delineation of the normative scheme, qualitative descriptive factors deduced from the statistical analyses of the attack probability data are introduced into the normative formulation. The addition of these descriptive elements is designed to corrupt the normative model so that the model becomes more descriptive of the human subjects' data. The addition of the descriptive factors to the normative formulation brings about the normative-descriptive model. It is the parameters of this normative-descriptive model that are tuned until the best possible fit between the model's output and the subjects' data is achieved.

The development of a normative-descriptive model (if it can be achieved) offers several advantages. Such a model yields a predictive tool of the subjects' decisionmaking. Thus, if one wished to determine the effects of varying the ranges of one or more input variables, such values can be passed to the model. If the original fit between the normative-descriptive model and the subjects' data was good, then good predictions on how subjects would behave, given the new input values would result. Following along in the same vein, the normative-descriptive model can be used to simulate the subjects' behavior in some larger more complex man-machine simulation environment. Thus the study of several decisionmakers and machine systems could be undertaken without the direct involvement of the actual decisionmakers and machine systems.

Perhaps, one of the most interesting and important advantages provided by the normative-descriptive model is the insights it affords of the subjects' decisionmaking processes. By carefully studying the constraints, biases, and processes that must be introduced into the normative formulation to capture the subjects' output behavior, insights into the actual decisionmaking processes used by the subjects are achieved. Such knowledge is invaluable in constructing a theory of human decisionmaking and understanding cognitive processes.

4.1 THE NORMATIVE FORMULATION

The task confronting the subjects in this experiment can be studied as a sequential estimation or cascading inference problem. Subjects must assess in a stage-or step-wise manner the probability that a certain detected missile (i.e., heat source) is a missile and then establish a probability that the missile is on an attack trajectory. The information subjects use to make the missile/ no missile decision is derived from the heat sensor readings. The information subjects use to determine the attack probability is based on their prior information (e.g., missile site attack probability) combined with the heat source's geographical position detected and reported three times at five minute intervals by a satellite radar system. These two sources of information are considered statistically independent, thus:

P(missile attack/heat sensor, geographic position) =

P(missile/heat sensor) • P(attack/geographic position)

or

$$P_{mA} = P_m \cdot P_A \qquad (1)$$

The heat sensor readings were generated randomly, and in all cases a missile was present, so it is assumed that $P_m = 1$ (note, that this will not be true for a general case). It is thus denoted:

$$P_{mA} = P_A = P$$

For each event, P is obviously a function of time that will be updated at each of the three reports.

P_O, the prior probability, is denoted as the directly observed missile site attack probability .

P_i, the posterior probability of attack after the geographical position of the missile (heat source) has been observed.

$$P_i = P(\text{attack})_i = P(\text{attack}/d = dA, i) \qquad (2)$$

where: i is the report number (i = 1,2,3)

$d_{A,i}$ is the orthogonal geometrically measured distance of the observed missile to the known attack trajectory eminating from the particular missile site (see Fig. 4-1). It is therefore postulated according to the one-step Bayesian theorem:

$$P(\text{attack})_i = P(\text{attack}/d_{A,i})$$

$$= \frac{P(\text{attack})_{i-1} \cdot P(d = d_{A,i}/\text{attack})}{P(\text{attack})_{i-1} \cdot P(d = d_{A,i}/\text{attack}) + P(\text{test})_{i-1} \cdot P(d = d_{T,i}/\text{test})} \tag{3}$$

where $d_{T,i}$ is the orthogonal geometrically measured distance of the observed missile to the known test trajectory. The problem is binary in nature (either attack or test), thus:

$$P(\text{test})_{i-1} = 1 - P(\text{attack})_{i-1}$$

and following the methodology presented so far:

$$P_i = \frac{P_{i-1} \cdot P(d = d_{A,i}/\text{attack})}{P_{i-1} \cdot P(d = d_{A,i}/\text{attack}) + (1-P_{i-1}) \cdot P(d = d_{T,i}/\text{test})} \tag{4}$$

or

$$P_i = \frac{P_{i-1}}{P_{i-1} + (1-P_{i-1})\ r_i} \tag{5}$$

where r_i is the likelihood ratio (for test)

$$r_i = \frac{P(d = d_{T,i}/\text{test})}{P(d = d_{A,i}/\text{attack})}$$

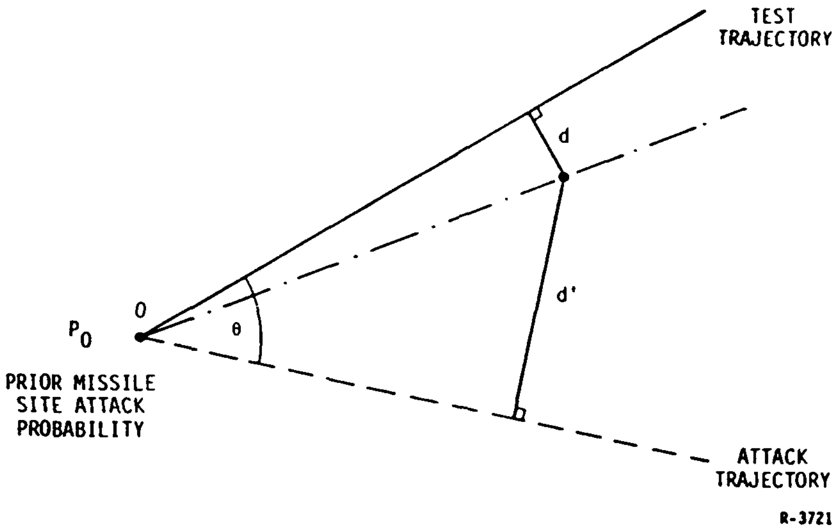

Figure 4-1. Computing the Deviations From the Test and Attack Trajectories Geometrically

The formulation presented in Eq. 5 represents a simple sequential recursive scheme to predict at any stage (i.e., report) the optimal posterior probability of attack (P_i) given the previous probability assessment (P_{i-1}) and the geometrically-based likelihood ratio (r_i). To provide a flexible parameter to the model, an exponential form for the likelihood function is assumed, thus:

$$\begin{cases} P(d = d_{T,i}/\text{test}) = e^{-\frac{d_{T,i}}{\alpha\Delta}} \\ \\ P(d = d_{A,i}/\text{attack}) = e^{-\frac{d_{A,i}}{\alpha\Delta}} \end{cases} \tag{6}$$

$$\text{where} \begin{cases} \Delta = 20 \text{ miles} \\ \alpha = \text{decay factor} \end{cases}$$

(An α equal to 3 would yield a 95 percent confidence interval, that the missile is in $\pm$ 1 Δ miles corridor about the respective trajectory.)

Given the above formulation, it can be stated that the likelihood ratio is:

$$r_i = e^{-\frac{1}{\alpha A}\left(d_{T,i} - d_{A,i}\right)} \tag{7}$$

The recursive formulation described in equations (5) and (7) were implemented and a set of three sequential optimal assessments of attack probabilities obtained for each event. The optimal attack probabilities derived from the normative model were then compared to the subjects' average attack probability estimates obtained experimentally. The comparison yielded an average RMS error of 0.232. Obviously, the subjects depart from optimality.

4.2 NORMATIVE-DESCRIPTIVE FORMULATION

The statistical analyses of the probability of attack data were carefully scrutinzed and several descriptive factors concerning the subjects' inference behavior identified. Essentially, the statistical results were examined for systematic error variance that could be attributed to the subjects. It was observed that the subjects showed a certain reluctance to assign a zero likelihood to what was an improbable attack (or test) given the size of the deviation from the respective trajectory. In other words, subjects increased the error corridor about each trajector well beyond the 20 mile deviation they were told to expect. Analyses revealed that subjects tended to extend the error corridor to approximately 40 miles (essentially $\pm$2 Δ miles) in each direction about the two trajectors. This "smudging" effect of the exponential curve describing the error deviation is shown in Fig. 4-2. Note that the normative formulation shows the 95 percent confidence interval to fall at 1 Δ miles (20 miles) on either side of a trajectory, while the curve describing the subjects shows the 95 percent confidence interval to fall at 2 Δ miles (40 miles).

To model this bias, a multiplicative factor β was introduced in the decay element of the likelihood formulation, thus:

$$P(d = d_{A,i}/\text{attack}) = e^{-\frac{d_{A,i}}{\alpha \cdot \beta \cdot \Delta}} \tag{8}$$

and

$$P(d = d_{T,i}/\text{test}) = e^{-\frac{d_{T,i}}{\alpha \cdot \beta \cdot \Delta}}$$

The value of β that provided the best fit to the subject data was equal to 2 (40 miles), as mentioned above.

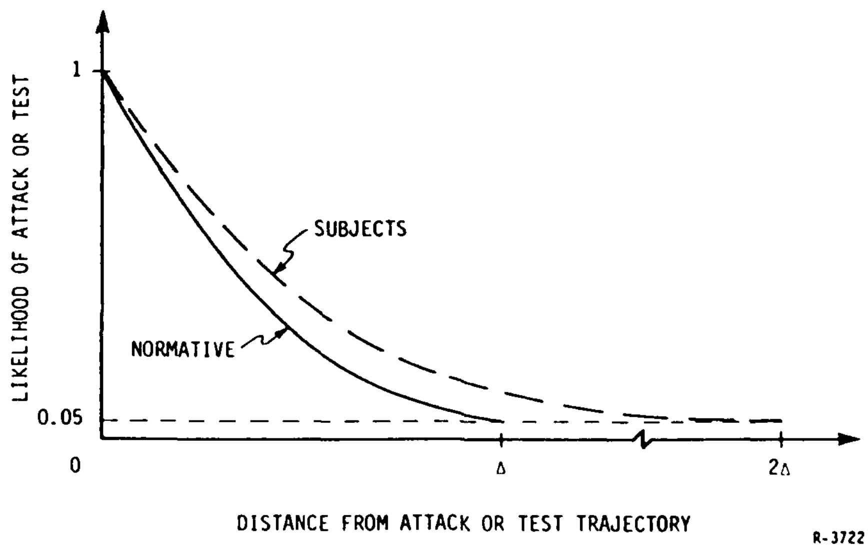

Figure 4-2. "Smudging" Effects on the Exponential Curve

Another observation that was made involved the subjects' tendencies to overweight the attack likelihoods with respect to the test likelihoods. Subjects seemed to enter the experiment with a bias in favor of attack. To capture this in the normative-descriptive formulation, a factor called γ was incorporated in the Bayesian equation (Eq. 5), thus:

$$P_i = \frac{P_{i-1}}{P_{i-1} + (1-P_{i-1})\gamma r_i} \quad . \tag{9}$$

The best value for γ was determined to be 0.8. That is, for an equal theoretical likelihood of attack or test, the subjects subjectively saw the odds as being 5:4 in favor of an attack.

Also observed were the subjects' attempts to obtain attack probability information from the heat sensor reading. As mentioned before, the heat sensor readings were (in reality) randomly determined and contained no such information. However, the analyses showed that subjects tended to be biased toward the mid-range values. As the heat sensor reading tended toward the mid-range values, subjects bias the attack probability estimates higher. It would appear that subjects combined, in probably a linear fashion, the missile probability (P_m, based on the heat sensor readings) with the attack probability (P_A, based on the geometrical deviations) such that:

$$P_{mA} = P_A \cdot \delta + P_m(1-\delta) \tag{10}$$

It should be noted that this linear combination of probabilities is mathematically incorrect, the correct form is a product, but this appears to be how the subjects do the combination. The best value for δ was found to 0.83.

Implementing the best values of the descriptive elements, the normative-descriptive model was employed to produce a set of three sequential assessments of attack probabilities for each event. A comparison of this set of attack probabilities, to that produced by the subjects, revealed an average RMS error of 0.04. This is within the magnitude of the sampling error about the subjects' attack probabilities and thus, represents a remarkably good fit.

SECTION 5

DISCUSSION

The signal detection analyses of both experiments indicate that subjects differing in cognitive style also differ in the way they make discriminations. Analytic subjects clearly discriminated better between attack and test situations than globals. Moreover, differences in memory ability between the two style groups cannot account for the differences in discrimination ability. The recognition memory analysis showed that analytics also made superior use of the incremental cue information present in each report update. The certainty (or confidence) results demonstrated that subjects were not any more certain of their probability ratings in attack or test situations.

These results are in consonance with the general definitions and respective expectations associated with analytic and global individuals. Analytics tend to differentiate their perceptual environment, experience items as discrete from their background, and thus are better able to focus on details that differentiated one environmental situation from another. Globals, on the other hand, tend to preceive their environment in a relatively undifferentiated manner, fuse parts of the perceptual field into a unified whole, and therefore are less sensitive to discrete changes in the environment, making it more difficult for them to decide if a situation represents an attack or a test. It should be noted that if a task required a situation to be considered globally, then globally oriented individuals would probably exhibit superior facility dealing with such a task. In other words, a critical determinant of behavior is the interaction of cognitive decision style with the specific environment. This is a point Lewin (1951) championed many years ago.

The ANOVA results demonstrated that prior information, such as the likelihood that an attack would be launched from a particular site, had a strong influence on the way subjects gauged the probability of attack. Missile site attack probability is apparently seen as quite concrete, subjects anchor on it, and weigh this source of information more than report updates and heat signature information. These results fit nicely with discussions concerning judgment by adjustment presented by Slovic, Fischhoff, and Lichtenstein (1977) and Tversky and Kahneman (1974). The subjects in this study adhered too tenaciously to the site probabilities and thus tended not to adjust their position as much as was warranted by the report information. Pitz (1974) has conjectured that anchoring is a key heuristic in describing how individuals create subjective probability distributions for uncertainties, and Graesser and Anderson (1974) hypothesize anchoring and adjustment as a method individuals employ to reduce strain when dealing with updating of probabilistic information.

Heat signature and report update information proved difficult for subjects to use. In truth, the heat signature data provided little or no useful information, however, few subjects recognized this fact. Most tried, albeit poorly, to extract information value from it. Heat signature data seemed most influential to making discriminations when readings were clearly out of range or in the error range. Subjects also seemed to turn to the heat signature data when the site probability was low. The latter finding implies that when the site probability information was not perceived as a good indicator of attack, subjects turned to other sources of information. The information that appeared most salient at the time apparently was the heat signature data, and subjects tried to use that information to help them discriminate between attack and test. In general, subjects attempted to index the likelihood of an attack and increased the probability of attack as the heat signature progressed from out of range, to in the error range, to in missile signature range.

The fact that information provided by report updates had the largest impact when other sources of information were weak is taken to mean that subjects had a difficult time dealing with uncertain probabilistic data. Subjects tended to undervalue the information present in the first and second reports and where possible use other sources of information. Possibly, these other sources of information were viewed as more reliable; however, this cannot be directly ascertained.

Modeling results tend to confirm the interpretations discussed above. When the normative formulation was corrupted to take account of the subject biases and heuristics, an excellent fit between the normative-descriptive model's estimate and the subjects' attack probability estimate was achieved.

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