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Combat Identification Decision Making: Effect of a Secondary Task

David J. Bryant

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Abstract

Two experiments used a dual task method to investigate whether compensatory and heuristic decision rules are based on distinct computational systems. Subjects learned to classify pictures of soldiers as friend or foe through trial-and-error learning then completed a test session designed to allow inference of subjects' decision strategies. In both experiments, subjects completed a condition in which they performed a simultaneous secondary task designed to consume executive working memory capacity [35], either at the time of test (Experiment 1) or during the training session (Experiment 2). In both cases, subjects exhibited slower responses when performing the secondary task than in a control condition, indicating that the secondary task competed for cognitive resources. The presence of the secondary task, however, produced significantly slower responses for those subjects classified as using a simple heuristic as opposed to a more complex compensatory strategy, which is consistent with research linking heuristics to a deliberate classification system and compensatory strategies to an automatic system. The secondary task manipulation, however, did not affect the proportions of subjects using the heuristic and compensatory decision rules. The results of two experiments suggest that heuristic and compensatory decision rules are mediated by different classification systems. The presence of competing cognitive demands, however, does not seem to affect whether a subject uses an heuristic or compensatory strategy.

Résumé

Deux expériences ont utilisé une méthode à double tâche pour étudier si des règles de décision compensatoires et heuristiques sont fondées sur des systèmes de calcul distincts. Les sujets ont appris à classer des photos de soldats en tant qu'amis ou ennemis par apprentissage par essai et par erreur et ont alors subi une séance de tests conçus pour permettre l'inférence des décisions sur les stratégies des sujets. Dans les deux expériences, les sujets étaient dans une situation dans laquelle ils exécutaient simultanément une tâche secondaire conçue pour utiliser la capacité de mémoire de travail exécutive [35], soit au moment du test (Expérience n^{o} 1) soit pendant la séance de formation (Expérience n^{o} 2). Dans les deux cas, les sujets ont réagi plus lentement lorsqu'ils exécutaient une tâche secondaire que dans une situation contrôlée, ce qui indique que la tâche secondaire était en compétition pour des ressources cognitives. La présence de la tâche secondaire toutefois, a entraîné des réponses considérablement plus lentes pour les sujets classés comme utilisant une stratégie heuristique simple en opposition à une stratégie compensatoire plus complexe, ce qui est conforme avec la recherche liant la stratégie heuristique à un système de classification délibéré et les stratégies compensatoires à un système automatique. La manipulation de la tâche secondaire, toutefois, n'a pas affecté les proportions de sujets utilisant des règles de décision heuristiques et compensatoires. Les résultats des deux expériences suggèrent que les règles de prise de décision heuristiques et compensatoires sont soumises à différents systèmes de classification. La présence d'exigences cognitives concurrentes, toutefois, ne semble pas affecter l'utilisation ou non par un sujet d'une stratégie heuristique ou compensatoire.

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Executive summary

Combat Identification Decision Making: Effect of a Secondary Task

David J. Bryant]; DRDC Toronto TR 2010-159; Defence R&D Canada – Toronto.

Introduction: Previous experiments have demonstrated that people can employ both heuristic and more complex compensatory strategies to classify targets as friend or foe [3][4][27]. One possible explanation why both types of strategy are used is that subjects may rely on different underlying classification systems which are conducive to different decision processes (e.g., [30][31][32]). One classification system is proposed to be deliberate and suited to learning rule-based distinctions, whereas the other is an implicit system that is automatic and suited to learning probabilistic cue associations. Thus, subjects who use an heuristic may rely on a deliberate, rule-based system, whereas others who use a compensatory rule may rely on an automatic, integrative system.

Results: Two experiments used a dual task method to investigate whether compensatory and heuristic decision rules are based on distinct computational systems. Subjects learned to classify pictures of soldiers as friend or foe through trial-and-error learning then completed a test session designed to allow inference of subjects' decision strategies. In both experiments, subjects completed a condition in which they performed a simultaneous secondary task designed to consume executive working memory capacity [35], either at the time of test (Experiment 1) or during the training session (Experiment 2). In both cases, subjects exhibited slower responses when performing the secondary task than in a control condition, indicating that the secondary task competed for cognitive resources. The presence of the secondary task, however, produced significantly slower responses for those subjects classified as using a simple heuristic as opposed to a more complex compensatory strategy, which is consistent with research linking heuristics to a deliberate classification system and compensatory strategies to an automatic system. The secondary task manipulation, however, did not affect the proportions of subjects using the heuristic and compensatory decision rules.

Significance: The results of two experiments suggest that heuristic and compensatory decision rules are mediated by different classification systems. Thus, subjects who use an heuristic may rely on a deliberate, rule-based system, whereas others who use a compensatory strategy may rely on an automatic, integrative system. The presence of competing cognitive demands, however, does not seem to affect whether a subject uses an heuristic or compensatory strategy.

Future Plans: Previous experiments have shown that differences in the specific associations of cues to friend or foe classification can produce markedly different patterns of decision strategy use by subjects. When the set of targets to be classified contain a highly predictive cue that is also highly salient, most subjects use an heuristic, whereas when the target set does not have a highly salient but predictive cue, most subjects prefer a compensatory strategy. Future experiments will examine whether this finding reflects some learning process that employs a rule-based or associative system depending on the availability of salient cues.

Sommaire

Prise de décision en identification au combat : Effet d'une tâche secondaire

[David J. Bryant]; RDDC Toronto TR 2010-159; R et D pour la défense Canada – Toronto

Introduction : Des expériences antérieures ont démontré que les personnes peuvent utiliser tant des stratégies heuristiques que des stratégies compensatoires plus complexes pour classer des cibles comme amies ou ennemies [3][4][27]. Une explication possible de l'utilisation des deux types de stratégie est que les sujets peuvent se fier à différents systèmes de classification sous-jacents qui sont favorables à différents processus de décision .(p. ex., [30][31][32]). Un système de classification est proposé pour être délibéré et adapté aux distinctions fondées sur des règles d'apprentissage, alors que l'autre est un système implicite qui est automatique et adapté aux associations de repères probabilistes de l'apprentissage. Donc, les sujets qui utilisent une stratégie heuristique peuvent se fier à un système délibéré, fondé sur des règles, alors que les autres qui utilisent une règle compensatoire peuvent se fier à un système automatique intégratif.

Resultats : Deux expériences ont utilisé une méthode à double tâche pour étudier si des règles de décision compensatoires et heuristiques sont fondées sur des systèmes de calcul distincts. Les sujets ont appris à classer des photos de soldats en tant qu'amis ou ennemis par apprentissage par essai et par erreur et ont alors subi une séance de tests conçus pour permettre l'inférence des décisions sur les stratégies des sujets. Dans les deux expériences, les sujets étaient dans une situation dans laquelle ils exécutaient simultanément une tâche secondaire conçue pour utiliser la capacité de mémoire de travail exécutive [35], soit au moment du test (Expérience n° 1) soit pendant la séance de formation (Expérience n° 2). Dans les deux cas, les sujets ont réagi plus lentement lorsqu'ils exécutaient une tâche secondaire que dans une situation contrôlée, ce qui indique que la tâche secondaire était en compétition pour des ressources cognitives. La présence de la tâche secondaire , toutefois, a entraîné des réponses considérablement plus lentes pour les sujets classés comme utilisant une stratégie heuristique simple en opposition à une stratégie compensatoire plus complexe , ce qui est conforme avec la recherche liant la stratégie heuristique à un système de classification délibéré et les stratégies compensatoires à un système automatique. La manipulation de la tâche secondaire, toutefois, n'a pas affecté les proportions de sujets utilisant des règles de prise de décision heuristiques et compensatoires.

Portée : Les résultats des deux expériences suggèrent que les règles de prise de décision heuristiques et compensatoires sont soumises à différents systèmes de classification. Donc, les sujets qui utilisent une stratégie heuristique peuvent se fier à un système délibéré fondé sur des règles, alors que les autres qui utilisent une stratégie compensatoire peuvent se fier à un système automatique intégratif. La présence d'exigences cognitives concurrentes, toutefois, ne semble pas affecter l'utilisation ou non par un sujet d'une stratégie heuristique ou compensatoire.

Recherches futures : Les expériences antérieures ont démontré que des différences dans les associations spécifiques de repères pour la classification ami ou ennemi peuvent entraîner des modèles de décision différents de façon marquée de la stratégie de prise de décision utilisée par les sujets. Lorsque le jeu de cibles à classer contient un repère hautement prédictif qui est aussi évident, la plupart des sujets utilisent une stratégie heuristique,alors que lorsque le jeu de cibles ne constitue pas un repère évident mais prédictif ,la plupart des sujets préfèrent une stratégie compensatoire. Les expériences futures examineront si cette découverte reflète un processus d'apprentissage quelconque qui utilise un système fondé sur des règles ou un système associatif selon la disponibilité de repères évidents.

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Acknowledgements

The experiments reported here were completed with the invaluable assistance of Sabrina Kanani.

Introduction

Background

Combat Identification (CID) is a basic military task in which one attempts to rapidly and accurately identify friendly, enemy and neutral forces. Formally, CID can be viewed as a cue-based categorization task in which a soldier categorizes one or more entities in the environment using whatever human perceptual and mechanical sensor cues are available. This can be a difficult task when no cue provides certain classification. Uncertainty results from flawed human perception and ambiguous sensor data, as well as inherent uncertainty as to which characteristics are important, or diagnostic, to the identity of targets can impair assessment [1][2]. This is especially true in asymmetric environments in which the enemy uses diverse equipment and attempts to blend into civilian populations, as well as in coalition operations in which allies may use different, unfamiliar equipment. Operating afield in unfamiliar nations often leaves soldiers with limited knowledge of the kinds of information needed to distinguish neutral from potentially hostile factions. In light of the importance of CID and the potential difficulty of the task, a precise understanding of the cognitive processes involved is needed to determine appropriate policies and procedures and to develop decision support systems.

Analytic Versus Heuristic Decision Processes

Previous research [3] [4] has examined the relative value of heuristics and analytic decision rules for CID [5]. Whereas an heuristic is a simple decision procedure that offers the potential to quickly and easily solve a specific problem, an analytic procedure promises an optimal solution at the cost of extensive computation and time. Both approaches have merits and both have received empirical support.

Analytic Processes

The analytic approach is based on the premise that human decision making can be modeled by normative theories of probability and logic. Normative theories explain human judgment in terms of explicitly computable processes to take in information, code it symbolically, manipulate these symbolic representations, and generate some output.

Analytic decision procedures based on these theories require some kind of formal comparison among decision alternatives using procedural rules that quantify those alternatives. Numerous specific procedures for comparing alternatives are known, most of which can be computationally modeled. Many, for example, are based on Bayesian statistics and evaluate options in terms of base rates for different hypotheses and probabilities of the accuracy of different observations [6]. Other analytic strategies include subjective expected utility analysis and feature-by-feature comparison (see [7]).

To make a judgment, an analytic procedure generally specifies a number of dimensions along which to compare alternatives. Typically, these computations are based on compensatory algorithms in which all dimensions are weighted [8]. A popular general form is the linear compensatory model (i.e. additive rule), which involves the computation of an overall score for each decision alternative based on the sum of relevant dimension values for each alternative, weighted by each dimension's importance [9]. Because the score of each alternative is based on all known dimensions, effects of large and small dimension values can compensate one another in determining the overall desirability of the alternative [10].

Analytic decision procedures are popular because they are designed to yield the optimal choice. The downside of such procedures, however, is that they must identify and compare all potential decision alternatives along all relevant dimensions. This means that analytic decision making entails extensive computations, even for fairly simple problems [11]. A comprehensive search for data to allow all comparisons is generally extremely time consuming, if not impossible, given limitations of human knowledge and cognitive capacity. Moreover, it may not be possible to construct a complete representation of the problem space, including a decision maker's goals, the values of potential outcomes, and the probabilities of certain actions producing certain outcomes [12].

Heuristic Processes

Heuristic models of decision making are based on the recognition that decision making mechanisms must work within the limits of time, knowledge, and computational power imposed by the situation and the decision maker him/herself [12][13][14]. Heuristics are informal, intuitive strategies that specify simple steps, which are often based on probabilistic data, and are designed to work under a few general assumptions [15] [16].

Fast and frugal heuristics are particularly simple heuristics for making judgments with limited information that have been shown to be accurate and efficient solutions to certain judgment tasks [17][18][19]. The Take the Best (TTB) heuristic, for example, performs two-alternative choice tasks by determining the single cue dimension that both discriminates options and has the highest validity (i.e., the cue offers the greatest conditional probability of indicating the correct choice given the cue's presence) [20][21]. In simulation studies with a variety of data sets drawn from psychology, economics, and other fields, TTB performs a choice task as accurately as more computationally intensive linear regression models [20][21]. In addition to achieving comparable accuracy, the TTB consistently exhibits a clear advantage over linear procedures in terms of frugality, consulting, on average, fewer cues and performing fewer computations than linear procedures. A non-compensatory heuristic such as TTB generally performs well when the task environment is itself structured such that the validity of cues falls off dramatically in a non-compensatory fashion [22].

Fast and frugal heuristics such as TTB can also provide plausible models of human decision making in tasks in which subjects are required to use probabilistically predictive cues to select an alternative (e.g., [23][24][25][26]). In these studies, however, only a subset (albeit a majority in some cases) of subjects can be classified as using TTB. Even under favourable conditions, subjects have frequently been observed to deviate from the principles of fast and frugal heuristics (e.g., [24][26]). Often, a significant proportion of subjects seem to use more complex, compensatory procedures in these experiments. Thus, it remains an open question as to the extent to which fast and frugal heuristics represent a general framework in which to understand human judgment.

Analytic and Heuristic Processes for Combat Identification

Given concerns that CID is vulnerable to problems of information overload and uncertainty [1], the fast-and-frugal heuristic approach provides a potentially useful framework in which to study time- and information-stressed decision making. Fast-and-frugal heuristics may be a natural means to manage a heavy information load in appropriate task environments.

To explore the potential of fast-and-frugal heuristics to model human threat assessment, Bryant [3] developed a simulated air threat assessment task (similar to CID) in which to compare predictions of different decision models. In three experiments, subjects learned to classify simulated aircraft using four probabilistic cues, then classified test sets designed to contrast predictions of several compensatory and non-compensatory heuristics. Various "contacts" (simulated aircraft) were presented on a simulated radar screen for subjects to classify as either friend or foe based on the values of four cues. Each cue value had a specific probability of being associated with friend and foe contacts, with these probabilities determining the cue's validity in classifying contacts.

To contrast different decision making models for CID, Bryant [3] [27] devised specific decision procedures for the threat classification task. Annex A provides a thorough description of these processes. Briefly, Take-the-Best-for-Classification heuristic (TTB-C) is a variant of TTB that identifies a target on the basis of the single most valid cue available. The Additive Rule (ADD) calculates the sum of unweighted cue values and selects the alternative with the highest score. The Weighted Additive Rule (WADD) is a variant in which cue values are weighted by the corresponding cue validities for each alternative prior to summation. A Bayesian classifier makes probabilistic inferences by applying Bayes' theorem through a network that represents the probabilistic relationships between threat class (friend or foe) and predictive cues. Given a set of cues, the network can be used to compute the probabilities of the target being a friend or a foe.

Bryant's [3] results indicated that about half of the subjects who exhibited a classifiable, non-random strategy appeared to use the non-compensatory fast-and-frugal heuristic TTB-C, but the other half used less frugal compensatory decision rules (i.e. either an additive or Bayesian rule). Interestingly, the relative proportions of subjects exhibiting responses consistent with the fast-and-frugal heuristic versus other decision rules was largely unaffected by manipulations of time pressure and perceived cue uncertainty. Only when a severe time pressure manipulation was employed did Bryant [4] observe a shift in group preference for an heuristic decision rule. When subjects were allowed only four seconds to respond, the majority of subjects employed either TTB-C or a guessing strategy, presumably because these strategies do not require time-consuming inspection of multiple cues. In contrast, when a control condition afforded sufficient time to examine all cues, subjects generally preferred strategies that made use of all available cues.

Bryant [4] examined other factors that might predict when decision makers will employ heuristics versus a Bayesian decision strategy. The way information is presented in a decision making task often has a significant impact on the way people perform that task. For example, a pictorial format may facilitate use of compensatory additive or Bayesian decision procedures because the visual system has mechanisms to rapidly sum cues or compute probabilities.

In one experiment, Bryant [4] contrasted subjects' performance when they learned to classify contacts using textual cues versus pictorial cues. Glöckner and Betsch [28] have suggested that heuristics, such as TTB-C, are associated with deliberate processing and should be strongly affected by conditions that increase task demands or reduce available cognitive resources. They further proposed that simultaneous availability of all cues is necessary to employ an automatic cue-integration procedure, which implies that subjects should be more likely to employ a Bayesian strategy when viewing pictures than when cues are provided textually. Text must be read sequentially, which would favour the use of a deliberate strategy, such as TTB-C. In Bryant's [4] experiment, however, substantial proportions of subjects in this experiment employed the TTB-C, ADD, and Bayesian rules, but there was no significant difference between the text and pictorial conditions in the proportions of subjects employing the Bayesian and TTB-C rules.

In a second experiment, Bryant (2009) sought to determine whether rapid presentation of pictorial stimuli affects the propensity of subjects to use a Bayesian decision strategy. If the Bayesian strategy depends on the recruitment of perceptual mechanisms, it may be more evident in situations in which the deliberate use of an heuristic is made difficult. Results of this experiment indicated that exposure time to pictorial stimuli did not affect the proportions of subjects employing heuristic versus compensatory decision rules.

Despite observing no effect of stimulus format or presentation time, one factor did have a profound impact on subjects' selections of decision strategy – the item set they studied. Bryant's [4] experiment employed two sets of items created from the same basic cues but varying the predictiveness of each cue across the different sets. In one set, the uniform was the most predictive cue and it also seemed to be the most perceptually salient. In the second set, the helmet was most predictive but this cue was not considered to be as salient as the uniform. It may be that when a perceptually salient cue, or a cue with a pre-existing association to the classification task, is also the most diagnostic, subjects are able to quickly notice its relation to classification and use a simple rule such as TTB-C. In contrast, when a non-salient cue is most predictive, subjects do not have one cue that immediately stands out as a key predictor and so they tend to look at all cues, which suggests a compensatory and analytic decision rule.

Automatic versus Deliberate Classification

A seeming problem for compensatory models of cue-based judgment is that they require fairly intense computation. The Bayesian model, for example, requires an individual to not only learn individual cue-criterion associations but also compute conditional probabilities, which is not something people consciously do in tasks such as CID. The limits of conscious information processing and working memory capacity seem incompatible with compensatory models. In contrast, heuristics are specifically designed to work with limited information and minimal information processing.

One possible way to reconcile the cognitive demands of compensatory models with their apparent use by some subjects in cue-based classification tasks is to assume that people are capable of performing compensatory computations automatically. Automaticity is often defined by three main criteria: insensitivity to intentional control, insensitivity to cognitive capacity limits, and absence of awareness [29]. With respect to this definition, an automatic process is one that a person performs without conscious control or awareness and which does not compete for limited cognitive resources. In contrast, a deliberate process is one in which processing is under conscious control, that the person has significant insight into (i.e. the person can describe how the process works), and is generally effortful and limited [28].

People may be able to employ two different processing systems to classify targets in CID. Ashby and colleagues [20] [31] [32] have argued that people possess two distinct systems for categorization. Specifically, they propose that people have access to both an explicit system that is deliberate and suited to learning rule-based class distinctions and an implicit system that is automatic and suited to learning how to integrate probabilistic cues to form categories. Evidence for this deliberate-automatic distinction comes from studies that have demonstrated that learning of rule-based classification schemes is strongly affected by cognitive load [33], task demands [34], and interfering tasks that compete for limited cognitive resources [30][35], whereas learning classification schemes based on integration of cues is largely unaffected by these factors.

The use of heuristics and compensatory decision rules can also be understood within the two-system framework. Heuristics, which are often framed in terms of simple rules (e.g., "take-the-best"), may associated with deliberate processing because they draw on controlled processes to apply simple rule-based judgments [36]. In contrast, compensatory rules, such as the Bayesian or WADD rules, may draw upon automatic processes. Glöckner and Betsch [28] have suggested that automatic processes driven by intuitive system enable persons to quickly integrate multiple reasons in decisions in a compensatory fashion. In three experiments, Glöckner and Betsch [28] found that subjects could employ the WADD strategy to perform a cue-based decision task as long as information search was not restricted. Moreover, subjects' response times were very fast, suggesting that performance was based on automatic processing.

It may be possible to better understand why some people employ heuristic decision rules in CID task whereas others employ a Bayesian procedure. According to the dual-system view, heuristics would be associated with deliberate rule-based processing. That is, to employ a heuristic such as TTB-C, one must consciously select a particular cue as the most valid and classify targets according to a simple rule. In contrast, the Bayesian procedure would be associated with automatic cue-integration. Subjects would not have to deliberately attempt to compute conditional probabilities but, rather, rely on automatic processes to integrate all available cues according to an algorithm that is consistent with Bayes' Theorem. Thus, different subjects could reveal different strategies depending on which classification system served as the basis for performance. This is consistent with Gigerenzer's concept of the "Adaptive Toolbox" in which people can choose an appropriate heuristic to suit a given problem [17]. What remains unclear is why some subjects would choose a deliberate heuristic and others an automatic compensatory strategy under the same experimental conditions.

The threat assessment task used by Bryant [3] is technically an information integration task because optimal performance depends on integration of all four cues. Thus, it might be expected that subjects would employ an automatic classification system, yielding judgments consistent with a Bayesian decision rule. Given the specific cue validities associated with cues, however, the maximum level of performance achievable with a heuristic such as TTB-C was almost the same as that of the Bayesian strategy. Thus, the task could be treated as a rule-based classification task with little discernable loss in accuracy. This allows subjects the option of approaching the task as either a rule-based or information-integration problem. The fact that the task is readily solvable by either procedure may explain why in most previous experiments there were subsets of subjects who preferred a heuristic-based solution and others who preferred a compensatory solution.

Dual Task Method

The nature of the processing system underlying human performance can be examined by the use of the dual task methodology. The logic of this methodology is based on the assumption that adding a secondary task to be performed simultaneously with a primary experimental task will increase the overall cognitive demands placed on a subject. The secondary task will compete for cognitive resources meaning the subject is able to devote less attention and computational resources to the primary task. This impairs performance of the primary task to the extent performance depends on those cognitive resources. In contrast to deliberate processes, automatic processes consume little if any attentional resources. Thus, a secondary task can be expected to selectively impair performance on tasks mediated by a conscious, deliberate processing system that requires active cognitive resources. The same secondary task, however, should have much less impact on performance of a task mediated by an automatic processing system.

This methodology has already been employed by Waldron and Ashby [30] to test predictions of their COVIS (COmpetition between Visual and Implicit Systems) model that proposes the existence of an explicit hypothesis testing system that is reliant on working memory and executive attention and an implicit procedural-learning system that operates independently of working memory (WM). They predicted that the explicit classification system, which relies on WM, would be negatively affected by competing demands for cognitive resources imposed by a concurrent task. In contrast, the implicit system should be able to operate with little if any impact because it does not require the cognitive resources being consumed by a concurrent task.

Using this logic, Waldron and Ashby [30] developed a numerical version of the Stroop task (see [37]) to serve as a secondary task. Subjects in their experiment were simultaneously presented with a target for categorization and a Stroop task stimulus. The Stroop stimulus would disappear after 200 msec while the target remained on screen until the subject indicated a categorization judgment. After that judgment, subjects then responded to the Stroop stimulus. The Stroop task required subjects to hold a representation of the stimulus in WM during the categorization process, thus competing for cognitive resources. To examine the impact of the secondary task on the two hypothesized categorization systems, Waldron and Ashby [30] employed one set of targets that could be classified along a single dimension or feature, which was predicted to elicit deliberate, rule-based categorization, and a second set requiring integration of three dimensions, which was predicted to elicit automatic procedural categorization. Consistent with their hypotheses, subjects' performance on the first uni-dimensional target set was significantly worse when concurrently performing the Stroop task relative to a control condition. In contrast, subjects' performance on the second, multi-dimensional target set was not affected by the concurrent task relative to a control condition. Taken together, these findings supported Waldron and Ashby's [30] claim that people can employ both a rule-based categorization system that requires WM and a procedural system that operates automatically and does not consume WM resources.

The experiments reported here use a dual task method to investigate whether compensatory and heuristic decision rules are based on distinct computational systems. Specifically, the selection of a heuristic versus compensatory decision strategy may depend on the nature of cognitive demands present when initially learning to classify targets.

Experiment 1

Bryant [4] observed an unexpected but very large effect of the specific target set of items on subjects' use of decision strategies. With Set 1, where the target's uniform was the most predictive cue and also seemed to be the most salient, a significant majority of subjects used the TTB-C heuristic. With Set 2, where the target's helmet was most predictive but not as salient as the uniform, a significant majority of subjects used the Bayesian or ADD rules. It may be that when a salient cue, or a cue with a pre-existing association to the classification task, is the most predictive subjects are able to quickly notice its relation to classification and use TTB-C. In contrast, when a non-salient cue is most predictive, subjects do not have one cue that immediately stands out as a key predictor and so they look at all cues to identify targets. This suggests a compensatory and analytic decision rule, either because subjects explicitly weigh all cues or because they acquire richer instances of contacts in memory, which supports a recognition-based decision rule that conforms to Bayesian predictions.

Although unexpected, the set effect provides a way to examine the processes underlying heuristic and analytic decision rules. Using Bryant's [4] target sets, it is possible to predict a priori what decision rule most subjects will adopt. With Set 1, most are expected to use TTB-C, whereas with Set 2, most will use the Bayesian or ADD rules. It is now possible to see whether a secondary task manipulation can alter those preferences.

In this experiment all subjects learned to classify friends versus foes as in previous studies then performed a test phase in one of two conditions. In the control condition, the test procedure was the same as that used by Bryant [4]. In the secondary task condition, subjects performed a simultaneous secondary task designed to consume executive WM capacity [35]. For each trial, secondary task stimuli, which are two different numerical digits from 1 to 9 printed in different font sizes, were presented concurrently to the left and right of a fixation point for 500 msec, followed by a rectangular coloured mask for another 500 msec. The test item followed and, after the subject made a friend or foe judgment, the word "value" or the word "size" appeared on the screen and the subject indicated on which side the number with the larger value or larger size was presented.

In contrast to deliberate processes, automatic processes are largely unaffected by increased attentional demands [28]. Thus, while having subjects complete a secondary dual-task while learning to classify contacts, we can expect that the secondary task will selectively impair deliberate processes due to competition for cognitive resources. Based on previous findings that associate heuristics with deliberate processing and additive or Bayesian rules with automatic processing, a competing demand on limited cognitive resources should make it more difficult to employ a heuristic but would not greatly affect the compensatory Bayesian or Additive decision rules. Thus, we would expect to see a larger population of subjects using the Bayesian rule than a heuristic-based rule in a dual-task condition.

It was predicted that, in the Control condition, subjects would show the Set 1/Set 2 difference observed by Bryant [4], in which most subjects used TTB-C with Set 1 but the Bayesian or Additive rule with Set 2. In the secondary task condition, however, it was expected that subjects would exhibit a strong preference for the Bayesian and Additive rules for *both* Set 1 and Set 2 because the secondary task would selectively interfere with the use of the deliberate heuristic strategy of TTB-C. The secondary task was not expected to affect the use of the automatic Bayesian and Additive decision rules.

Method

Subjects

Subjects were 48 male and female volunteers who were employees of Defence Research and Development Canada - Toronto (DRDC Toronto), students conducting research at DRDC Toronto, individuals recruited from local universities, or reserve force soldiers. All subjects were aged 18 and older, had normal or corrected-to-normal vision, and were unfamiliar with the specific hypotheses and stimulus configurations of the experiments. All received stress pay remuneration for participating.

This study, approved by the DRDC Toronto Human Research Ethics Committee (HREC), was conducted in conformity with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans.

Materials

The experiment was conducted with Personal Computers (PCs) using the E-Prime experiment authoring software. The software presented instructions and stimuli, collected subject responses, and recorded data.

Figure 1: Examples of stimuli

In the experiment, subjects learned to classify potentially hostile soldiers (contacts) as friend or foe. The contacts were presented in pictorial format, as illustrated in Figure 1. Each contact's identity was determined by the combination of four characteristics (cues) – the pattern and colour of the contact's uniform (CADPAT[1] or olive green), the presence of a face covering (black mask or no mask), the type of rifle held (C7 or AK-47), and the colour of the helmet (Canadian or dark green). Each contact's cue values were generated according to a probability matrix (i.e., each cue value will have a specified probability of being associated with each class of contact, hostile and non-hostile).

Subjects performed two conditions, a control and a secondary task condition. Consequently, two sets of 300 contacts (150 friend and 150 foe) were used for the training sessions and two sets of 100 contacts (50 friend and 50 foe) were created for the test sessions. The training sets were identical to those used by Bryant [4]. The sets were counter-balanced across conditions.

Design

Three variables were manipulated in this experiment. The first, varied within subjects, was the Cue Validity of each cue used to describe contacts in the training stimuli sets. To vary Cue Validity, each possible value of a cue (values 1 and 2) was probabilistically associated to friend and foe classifications such that each cue differed in diagnosticity. Thus, for one cue each possible value was paired with the friend or foe classification 90% of the time, for another cue 80% of the time and so on. Table 1 indicates the proportions of friend and foe contacts possessing each cue value for the four cues in the two training sets.

Table 1. Relative Frequencies of Cue Values for Friend and Foe Contacts

	SET 1							
	Cue 1 (Uniform)		***Cue 2 (Helmet)***		***Cue 3 (Rifle)***		***Cue 4 (Face Cover)***	
	Value 1 *(CADPAT)*	***Value 2 (Olive)***	***Value 1 (Can.)***	***Value 2 (Dark gr.)***	***Value 1 (C7)***	***Value 2 (AK-47)***	***Value 1 (None)***	***Value 2 (Covered)***
Friend	90%	10%	60%	40%	30%	70%	20%	80%
Foe	10%	90%	40%	60%	70%	30%	80%	20%
	SET 2							
	Cue 1 (Helmet)		***Cue 2 (Uniform)***		***Cue 3 (Face Cover)***		***Cue 4 (Rifle)***	
	Value 1 (Can.)	***Value 1 (Can.)***	***Value 1*** *(CADPAT)*	***Value 2 (Olive)***	***Value 1 (None)***	***Value 2 (Covered)***	***Value 1 (C7)***	***Value 2 (AK-47)***
Friend	90%	10%	60%	40%	30%	70%	20%	80%
Foe	10%	90%	40%	60%	70%	30%	80%	20%

[1] CAnadian Disruptive PATtern (CADPAT).

A contact was created by, first, designating it a friend or foe, then assigning values to each of the four cues according to the probabilities in Table 1. For example, in Set 1 a friend would be assigned a value for uniform (cue 1) of either "CADPAT" (90% chance) or "Olive" (10% chance), a value for helmet (cue 2) of either "Canadian" (60% chance) or "Dark Green" (40% chance) and so on. A foe in Set 1 would be assigned values for the same four cues but the probabilities for each value were reversed. Contacts in Set 2 were created in the same manner by Bryant (2009) but probability values associated with each cue were different (see Table 1).

The second variable manipulated was the Contact Type in the test stimuli. Each test set was made up of patterns that offered contrasting predictions of the four contending classification strategies discussed previously; namely TTB-C, the Bayesian strategy, and the ADD and WADD rules. Eight cue patterns were identified for which at least one strategy offered a differing response than predicted by the other strategies. From these contacts, we created six Contact Types (A, B, C, D, E, and F) that distinguished the predicted accuracy of the possible strategies. The different item types are indicated in Table 2 with the predicted response of each decision strategy. Note that each cue pattern listed in Table 2 falls into a different Contact Type depending on whether that pattern is associated to a friend or foe. Type A and B items elicit opposing predictions from TTB-C and the Bayesian strategy. Where TTB-C would predict that these patterns indicate a friend, the Bayesian strategy would predict they indicate a foe, and vice versa. Type C and D patterns elicit the same predictions from TTB-C and the Bayesian strategy but force the ADD rule to guess because equal numbers of cues suggest friend and foe classifications. Types E and F contacts distinguish the WADD and ADD rules.

Table 2: Predicted Responses to Contact Types by Hypothesized Strategies

	Predicted Response of Strategy				**Contact Types**	
Cue Pattern	**TTB-C**	**Bayesian**	**WADD**	**ADD**	**Foe**	**Friend**
1,2,1,1	Foe	Friend	Friend	Friend	B	A
2,1,2,2	Friend	Foe	Foe	Foe	A	B
1,1,1,1	Foe	Foe	Guess	Guess	D	C
2,2,2,2	Friend	Friend	Guess	Guess	C	D
1,2,2,1	Friend	Friend	Friend	Guess	F	E
1,2,1,2	Friend	Friend	Friend	Guess	F	E
2,1,2,1	Foe	Foe	Foe	Guess	E	F
2,1,1,2	Foe	Foe	Foe	Guess	E	F

Note: Cue pattern indicates the value (as 1 or 2) for each cue in order of cues under Set 1 in Table 1

In the test set, each of the critical patterns was paired an equal number of times with friend and foe contacts. We predicted the levels of accuracy predicted by the hypothesized decision procedures for each Contact Type, shown in Table 3.

Table 3: Predicted Accuracy Levels by Contact Type

	Contact Type					
Heuristic	**A**	**B**	**C**	**D**	**E**	**F**
TTB-C	100%	0%	100%	0%	100%	0%
Bayesian	0%	100%	100%	0%	100%	0%
Weighted Pros Rule	0%	100%	Guess	Guess	100%	0%
Unweighted Pros Rule	0%	100%	Guess	Guess	Guess	Guess

The third variable, varied within subjects, was Task Condition. The Control condition replicated the procedure used in previous studies (Bryant, 2007, 2009) in which subjects completed only the classification task. In the Secondary Task condition, subjects performed the same classification task but also had to perform a secondary task during the test phase.

Procedure

The experiment was divided into two sessions for the Control and Secondary Task conditions, each with a training and test phase. In the training phase of both conditions, subjects viewed 300 contacts (pictures of soldiers), of which 150 were friends and 150 foes. Given the structure of cue information, some patterns were more likely to occur than others through a random generation of contacts and the training set contained a number of each pattern proportional to its expected frequency. The contacts were presented sequentially and a contact did not appear until the subject had made a response to the previous contact. For each contact, the subject made a classification judgment, indicating that the contact is either hostile or not hostile by pressing a labeled key on the computer keyboard. No other options were presented and subjects had to make a decision for each stimulus. After making his/her response, the subject was given accuracy feedback on their classification judgment in the form of a message indicating whether they were correct or incorrect and provision of the correct classification. Subjects received no initial information concerning the predictiveness of cues and all learning was accomplished through trial-and-error.

Following the training phase, subjects were allowed a short break and then performed the test phase. The test phase followed the same procedure as the training phase with a few important differences. First, subjects received no feedback on the accuracy of their judgments. Second, subjects were presented with only 100 contacts (10 each of type A, B, C, D, E, and F, and 40 randomly selected from all other patterns). Subjects were required to respond to all contacts. If, however, a subject had not responded within 16 sec, a null response was recorded and the next contact presented.

In the Secondary Task condition, subjects performed a secondary executive WM task simultaneous with the classification task (Zeithamova & Maddox, 2006). For each trial, secondary task stimuli, which were two different numerical digits from 1 to 9 printed in different font sizes, were presented concurrently to the left and right of a fixation point for 500 msec, followed by a rectangular coloured mask for another 500 msec. The test item followed and the subject made a friend or foe judgment by pressing the appropriate labeled key on the keyboard. Once the subject had responded, the word "value" or the word "size" appeared on the screen and the subject indicated on which side of the screen the number with the larger value or larger size had been presented, again by pressing the appropriate labeled key on the keyboard. The procedure was repeated for all 100 test items.

Results

Training Session

The contacts presented during the training session were divided into six blocks of 50 contacts each based on the order of presentation (i.e., the first 50 contacts, the next 50, etc.). Accuracy scores (the percentage of contacts correctly classified as friend or foe) were calculated for each block for each subject to create mean accuracy scores, which are shown broken down by Task Condition in Figure 2. Overall, subjects' mean accuracy in the final block was somewhat lower than that seen in previous experiments [3] and significantly less than the optimal levels of performance predicted by any of the decision models under consideration (0.91).

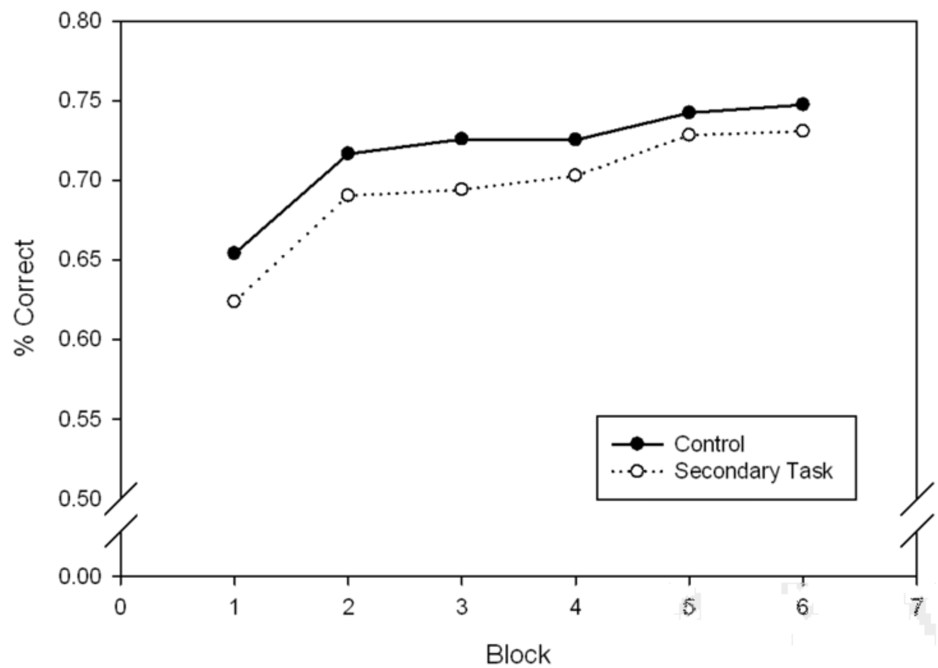

Figure 2: Classification Accuracy by Block in the Training Session

A mixed-design Analysis of Variance (ANOVA) revealed a significant effect of Training Block [$F(5,230) = 20.75$, MSe = .006, $p < .01$] but no significant main effect of Task Condition [$F(1,46) = 1.67$ MSe = .05, *n.s.*], which was expected because the training sessions were the same in both cases. There was likewise no significant interaction effect between the two factors [F(5,230) = 0.16, MSe = .008, *n.s.*].

The training item set used was examined as a categorical factor to determine whether one set might be easier to learn to classify. There was a significant main effect of training set [F(1,46) = 16.45 MSe = .05, p < .05], and this factor also interacted with Training Block [F(5,230) = 20.75, MSe = .006, p < .05]. Subjects exhibited greater accuracy overall when learning to classify Set 1, although no such advantage was observed by Bryant [4] for the same sets of items with the same training procedure. The interaction effect seems to be the result of subjects' accuracy levels being roughly equal for Sets 1 and 2 in the first training block but slightly higher for Set 1 than Set 2 in all subsequent blocks. This result also contrasts with that of Bryant [4] who observed somewhat higher levels of accuracy for Set 1 in the early training blocks (1-4) but roughly equivalent accuracy in the final two blocks.

A second mixed-design ANOVA was performed on subjects' mean response times to contacts across blocks. This analysis revealed a significant effect of Training Block [F(5,230) = 33.32, MSe < .001, p < .01] as subjects tended to respond faster over the course of the training session. No other factor or interaction significantly affected response times in the training session.

Test Session

Classification Strategy

Each test set was made up entirely of patterns that offered contrasting predictions of the contending classification strategies (see Table 2). Type A and B items, for example, elicit opposing predictions from TTB-C and the Bayesian strategy. Type C and D patterns elicit the same predictions from TTB-C and the Bayesian strategy but force the ADD and WADD rules to guess because equal numbers of cues, with equal combined weights, suggest friend and foe classifications. The purpose of the different item types was to allow the maximum contrast of predictions made by the decision rules under consideration.

To infer which decision rule subjects' employed to classify test items, we adopted Bröder and Schiffer's [24][38] Maximum Likelihood Method (MLM) which compares each subject's response for each item of each pattern (A, B, C, D, etc.) to the predicted responses of each decision rule (TTB-C, Bayesian, etc.). Their method calculates, based on the proportion of subjects' responses that conform to a given decision rule, the precise likelihood that a decision strategy produced a subject's pattern of responses. The MLM chooses the best fitting model from TTB-C, Bayesian, ADD, WADD, and guessing based on the likelihood that a subject's responses were generated by each strategy. The MLM is explained in more detail in Annex B, which indicates the equations by which MLM computes, for each strategy, the conditional probability of the subject's responses being produced by that strategy.

Table 4 presents the number of subjects classified as using a given decision strategy. As can be seen, the proportions of subjects using each of the decision strategies were very similar in the Control and Secondary task conditions and a Pearson Chi-Square test revealed no significant difference between the two conditions [$\chi 2$ =8.40, df = 4, n.s.]. These results are similar to those obtained by Bryant [4].

Table 4: Number of Subjects Classified as Using Hypothesized Decision Strategies

	Decision Procedure				
Condition	**TTB-C**	**Bayesian**	**ADD**	**WADD**	**Unclassifiable**
By Task Condition					
Control	25	14	7	1	1
Secondary task	21	11	5	1	10
By Item Set					
Set 1	35	4	3	1	5
Set 2	11	21	9	1	6

N = 48 for each presentation format & target set

The two target sets comprised different associations of cues with friend/foe classification. That is, although the same four cues were used in both sets, these cues were associated with different classifications and/or had different cue validities in the two sets. To assess the effect of the cue configuration of a target set, we collapsed strategy use across Task Condition and separated it according to the target set. The numbers of subjects classified as using a given strategy for each target set are shown in Table 4. As can be seen, subjects tended to use TTB-C when dealing with Set 1 and the Bayesian and Additive rules when dealing with Set 2 [$\chi 2$ = 27.17, df = 4, p<.05]. This result replicated the set effect seen in Bryant [4].

The critical comparison for this experiment is between the two sets in the Secondary Task condition. Table 5 shows the numbers of subjects using each of the various decision procedures broken down by condition and item set. If the presence of a secondary task selectively interferes with the use of an heuristic, we would expect few subjects to employ TTB-C for either Set 1 or Set 2 in the Secondary task condition. This would be indicated by a change in the number of subjects using TTB-C for Set 1. Whereas in the Control condition most subjects used TTB-C for Set 1, we expected the secondary task to reverse the numbers of subjects using TTB-C compared to the Bayesian and additive rules for Set 1.

Table 5: Number of Subjects Classified as Using Hypothesized Decision Strategies

	Decision Procedure				
Condition	**TTB-C**	**Bayesian**	**ADD**	**WADD**	**Unclassifiable**
Control – Set 1	19	2	2	1	0
– Set 2	6	12	5	0	1
Sec. task – Set 1	16	2	1	0	5
– Set 2	5	9	4	1	5

N = 48 for each presentation format & target set

This comparison is highlighted in Table 5. Clearly, in the Secondary task condition, the majority of subjects favoured TTB-C over the other decision procedures for Set 1, just as in the Control condition. Thus, although the secondary task affected subjects' responses – slowing responses significantly when they used TTB-C – it did not affect which strategy they used. Despite the added cognitive load, subjects still tended to prefer the TTB-C heuristic for Set 1.

Response Time

Response times were measured after the contact disappeared from the screen from the time at which the decision prompt appeared to the time at which the subject pressed either the friend or foe key on the computer keyboard. Mean response times are shown in Table 6. Generally, subjects required less than a second to make their responses in both Control and Secondary Task conditions.

Table 6. Mean Response Times (ms) and Standard Deviations of the Mean to Test Items

		Item Type						
		All	**A**	**B**	**C**	**D**	**E**	**F**
Control								
Set 1	**Mean**	603	628	599	573	593	620	605
	SD	*184*	*144*	*263*	*169*	*166*	*180*	*179*
Set 2	**Mean**	600	615	639	629	585	613	515
	SD	*183*	*178*	*255*	*233*	*120*	*172*	*140*
Total	**Mean**	601						
	SD	*187*						
Secondary task								
Set 1	**Mean**	841	882	885	815	772	815	878
	SD	*277*	*287*	*290*	*277*	*222*	*299*	*286*
Set 2	**Mean**	876	900	912	851	765	954	875
	SD	*250*	*326*	*306*	*188*	*206*	*225*	*247*
Total	**Mean**	859						
	SD	*267*						

Subjects' reaction times were not distributed normally so a transformation of all mean response times by their natural log was performed prior to analysis. The natural logs of mean response times preserves the ratio scale of means but compresses the variability associated with them. A mixed-design ANOVA revealed a significant effect of Task Condition [$F(1,46) = 92.78$, $MSe = 0.20$, $p < .01$] and subjects were significantly faster to respond in the Control than Secondary task condition. The ANOVA revealed no other significant main or interaction effects of other variables. This result supports the conclusion that the secondary task did successfully compete for cognitive resources with the classification task.

To further explore the impact of the secondary Task on classification, mean response times were computed within the Control and Secondary task conditions according to the decision strategy assigned to subjects.[2] Thus, all the subjects inferred to have used TTB-C were grouped together, all inferred to have employed the Bayesian rule grouped, and so on, then their mean response times compared to assess how they differed within and between conditions. Figure 3 shows these mean response times for the ADD, Bayesian, and TTB-C strategies (means for the WADD rule are not shown because only two subjects were assigned this strategy). As can be seen in this figure, subjects' responses were slower in the Secondary task than Control condition regardless of which strategy was employed. It is also apparent, however, that the secondary task manipulation had a greater interfering effect when subjects employed the TTB-C heuristic as opposed to one of the compensatory decision rules (ADD, Bayesian).

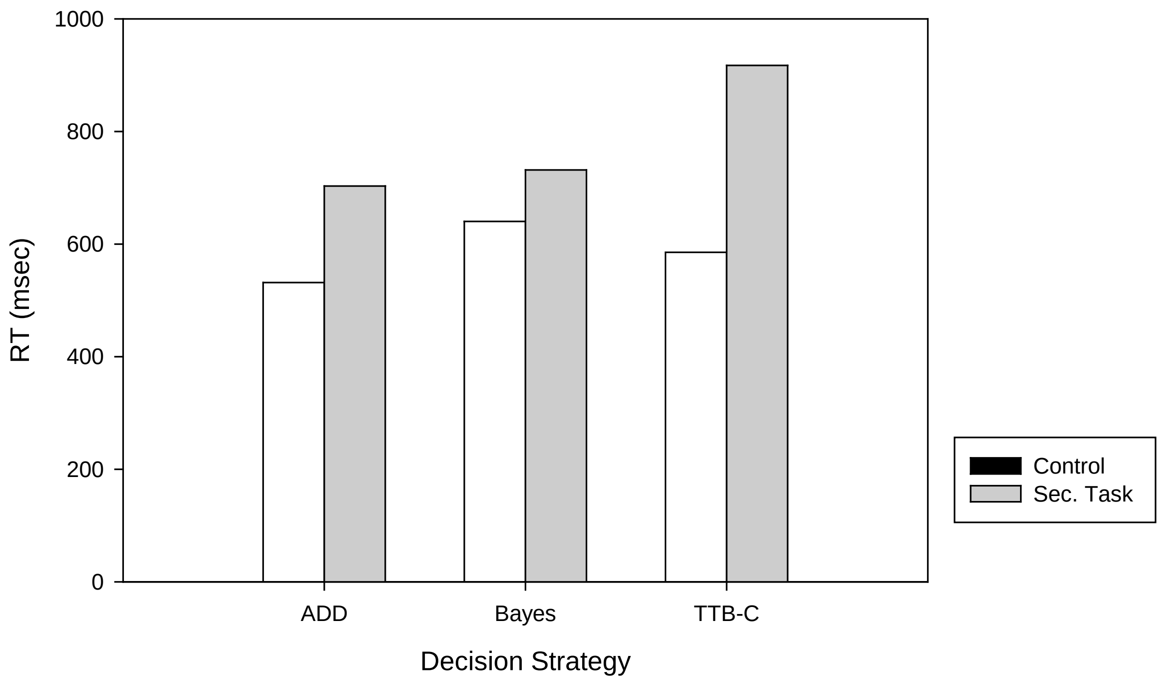

Figure 3. Mean Response Times (msec) to Test Items by Assigned Decision Strategy.

Separate mixed ANOVAs were performed for the Control and Secondary Task groups. In the analysis of the Control condition, Item Type served as the within-subject variable and the decision strategy adopted by subjects in the Control condition as a categorical variable. For the analysis of the Secondary task condition, strategy adopted in the Secondary task condition was the categorical factor. The Control ANOVA revealed no main effect of decision strategy [$F(1,43) = 1.59$, $MSe = 0.40$, n.s.] or of Item Type [$F(1,215) = 0.90$, $MSe = 0.06$, n.s.] and these factors did not significantly interact [$F(20,215) = 0.62$, $MSe = 0.06$, n.s.]. In contrast, the Secondary task ANOVA revealed a significant effect of decision strategy [$F(1,43) = 4.01$, $MSe = 0.26$, $p < .01$], although neither Item Type [$F(5,215) = 0.79$, $MSe = 0.07$, n.s.] nor the interaction of factors [$F(20,215) = 1.57$, $MSe = 0.07$, n.s.] produced significant effects.

[2] This analysis excluded subjects who's decision strategy could not be classified.

To determine the specific effects of the Secondary task manipulation on subjects using each of the different decision strategies, we performed a series of independent t-tests. For the purpose of comparing mean response times between decision strategies, the ADD and Bayesian strategy groups were combined into a single compensatory strategy group. This was deemed necessary to produce a combined group that possessed a number of data points roughly on par with the number in the TTB-C group. Combining the ADD and Bayesian groups was deemed appropriate because their mean response times were similar in both the Control and Secondary task conditions. Mean response time for subjects using TTB-C in the Control condition did not differ from that of subjects using a compensatory strategy in the Control condition [$t(44) = 0.51$, n.s.]. In contrast, mean response time for the Secondary Task TTB-C group was significantly greater than that of the Control TTB-C group [$t(44) = 6.91$, $p < .05$]. A similar significant difference was found between the Secondary Task compensatory and Control compensatory groups [$t(36) = 2.39$, $p < .05$]. Finally, mean response time was significant greater for the Secondary task TTB-C group than the Secondary task compensatory group [$t(36) = 3.30$, $p < .05$], indicating that the Secondary task manipulation had a greater impact when subjects employed TTB-C than when they employed a compensatory strategy such as ADD or the Bayesian rule.

Discussion

The main hypothesis of this experiment was that performing a simultaneous secondary task while performing the friend-foe classification task would alter subjects' selection of a decision strategy. More specifically, we predicted that the secondary task would selectively interfere with the use of the heuristic TTB-C because heuristics are associated with deliberate, rule-based processing. In fact, we found no evidence that the secondary task manipulation had any effect on which decision rules subjects employed in the test phase. The secondary task was apparently successful in competing for cognitive resources with the main classification task. Subjects were slower on the classification task in the secondary task condition than the control condition. Thus, the absence of an effect on the proportions of subjects using heuristic versus compensatory decision strategies does not seem to be due to an inadequate competing task.

Looking at response times as a function of the decision rule used by subjects, we see that subjects responded slower in the secondary task condition regardless of the decision rule used. There was, however, a significant interaction effect between decision rule and task condition. Performing contrasts between the control and secondary task conditions for each decision rule, we found that the differences for the ADD and Bayesian rules were not significant. For those subjects using TTB-C, however, responses were significantly slower in the secondary task condition than the control. These results are consistent with Glöckner and Betsch [28] and suggest that TTB-C is a deliberate, effortful strategy, whereas the Bayesian and Additive rules take advantage, to some degree, of automatic processing.

Experiment 2

Adding a secondary task to the test phase did not affect subjects' preferences for heuristic or compensatory decision strategies in Experiment 1. Thus, the demands at the time of test do not seem to be a key factor in determining which strategy a subject will use. It may be, however, that competing cognitive demands have even more impact on the initial choice of a decision strategy while the subject is learning to classify targets. In this experiment, we added the secondary task to the training session. Subjects are likely to select a decision strategy during training, so a secondary task may have a greater impact on strategy selection during the training session than test session.

Method

Subjects

Subjects were 48 male and female volunteers who were employees of DRDC Toronto, students conducting research at DRDC Toronto, individuals recruited from local universities, or reserve force soldiers. All subjects were aged 18 and older, had normal or corrected-to-normal vision, and were unfamiliar with the specific hypotheses and stimulus configurations of the experiments. All received stress pay remuneration for participating.

This study, approved by the DRDC Toronto HREC, was conducted in conformity with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans.

Materials

The experiment was conducted with PCs using the E-Prime experiment authoring software. The software presented instructions and stimuli, collected subject responses, and recorded data. The experimental task and stimuli were the same as those used in Experiment 1.

Design

Three variables were manipulated in this experiment. The first two, Cue Validity and Contact Type, were the same as in Experiment 1. The same training and test sets were employed in the current experiment, yielding the same predicted levels of accuracy for the various decision strategies (see Table 3). The third variable, varied within subjects, was Task Condition. In this experiment, this variable refers to the presence of a secondary task during the training rather than test phase. The Control condition replicated the procedure used in Experiment 1 and subjects completed only the classification task during training and test phases. In the Secondary Task condition, subjects performed the same classification task during training but also had to perform a secondary task designed to compete for executive WM resources. For both conditions, subjects performed the test phase without a competing task.

Procedure

The experiment followed the same procedure as Experiment 1 except that subjects performed the secondary task during training in the Secondary Task condition, and not in the test phase.

In the training phase of the Control condition, contacts were presented sequentially and a contact did not appear until the subject had made a response to the previous contact. For each contact, the subject made a classification judgment, indicating that the contact was either hostile or not hostile by pressing a labeled key on the computer keyboard. No other options were presented and subjects had to make a decision for each stimulus. After making his/her response, the subject was given accuracy feedback on their classification judgment.

In the training phase of the Secondary Task condition, participants performed a simultaneous secondary task in addition to the combat identification task for 300 contacts. On each trial, two different numerical digits from 1 to 9 were printed in different font sizes for 1000 msec on the screen. The contact then appeared on the screen for 500 msec followed by a coloured mask for another 500 msec. Participants were then prompted to categorize the contact as friend or foe by pressing a labeled key on the keyboard. After this, feedback was given on classification judgment in the form of a message indicating whether the response provided was correct or incorrect. Then either the word “value” or the word “size” appeared on the screen and the participant was required to indicate on which side the number with the larger value or larger size was presented by pressing an appropriately labeled key on the keyboard.

Following the training phase, subjects were allowed a short break and then performed the test phase. The test phase for both conditions followed the same procedure as the test procedure of the Control condition in Experiment 1.

Results

Training Session

Accuracy

The contacts presented during the training session were divided into six blocks of 50 contacts each based on the order of presentation. Mean accuracy scores are shown broken down by Task Condition in Figure 4. Overall, subjects’ mean accuracy in the final block was higher than that seen in the previous experiment but still significantly lower than the optimal levels of performance predicted by any of the decision models under consideration (0.91).

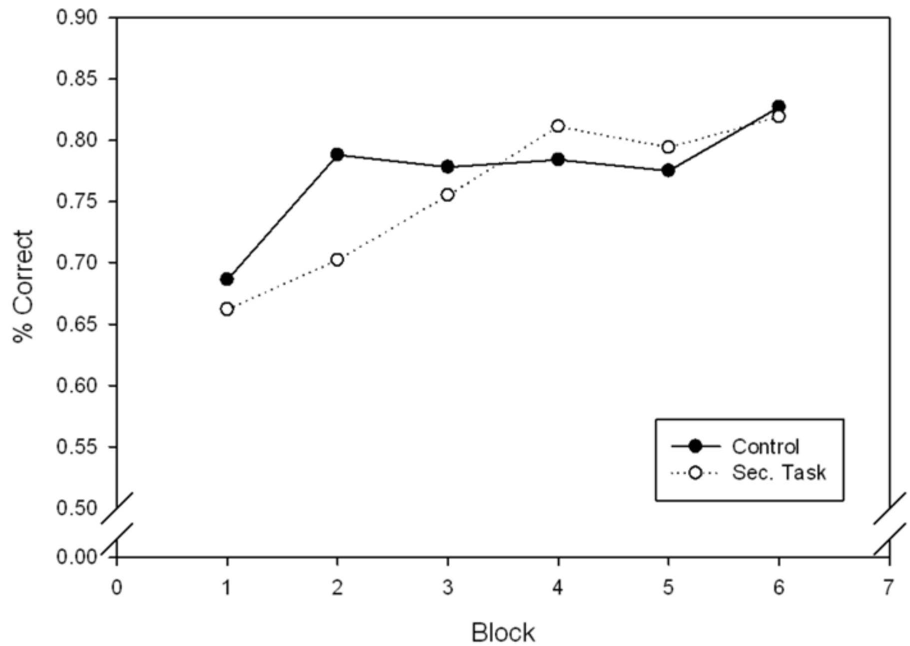

Figure 4: Classification Accuracy by Block in the Training Session

A mixed-design Analysis of Variance (ANOVA) revealed a significant effect of Training Block [F(5,230) = 40.74, MSe = .006, p < .01] but no significant main effect of Task Condition [F(1,46) = 0.55 MSe = .07, *n.s.*]. The latter result indicates that subjects were able to achieve the same overall level accuracy in the Secondary Task and Control conditions, despite the greater demand placed on subjects in the Secondary Task condition. A significant interaction effect was observed between Task Condition and Block [F(5,230) = 4.88, MSe = .008, p < .01]. Subjects exhibited lower accuracy during the first three blocks in the Secondary Task condition than the control condition but roughly the same, or slightly higher, accuracy during the final three blocks. Thus, the secondary task seems to have made the categorization learning somewhat more difficult initially, although subjects eventually learned to classify friends and foes equally well in both conditions.

The training item set used was examined as a categorical factor to determine whether one set might be easier to learn to classify. In contrast to the result observed in Experiment 1, there was no significant main effect of Training Set [F(1,46) = 0.46 MSe = .05, *n.s.*]. Training Set did, however, interact with Training Block [F(5,230) = 2.84, MSe = .006, p < .05]. Additionally, the three-way interaction of Training Set, Task Condition, and Block was also statistically significant [F(5,230) = 3.33, MSe = .008, p < .01]. In the Control condition, accuracy levels were generally equal across blocks for Sets 1 and 2 but somewhat greater accuracy was observed for Set 2 in Block 3 and for Set 1 in Block 6. In the Secondary Task condition, accuracy levels were essentially the same for Sets 1 and 2 in Blocks 1 to 3 but somewhat higher for Set 1 in Blocks 4 to 6. These differences do not appear to reflect any readily interpretable pattern.

Subjects' accuracy was examined as a function of the decision strategy adopted by the subject, as inferred through the classification strategy in the test session (see below). Separate mixed ANOVAs were conducted for the Control and Secondary Task conditions with Block as a within-subject factor and Decision Strategy as a categorical factor (subjects whose decision strategy could not be classified were excluded from these analyses). Decision strategy was found to not affect accuracy in either the Control [$F(4,43) = 1.83$ $MSe = .06$, *n.s.*] or Secondary task [$F(1,46) = 1.25$ $MSe = .05$, *n.s.*] conditions.

Response Time

A mixed-design ANOVA was performed on subjects' mean RTs across blocks. This analysis revealed significant effect of Training Block [$F(5,235) = 36.89$, $MSe < .001$, $p < .01$], as subjects tended to respond faster over the course of the training session, and Task Condition [$F(1,47) = 20.10$, $MSe < .001$, $p < .01$], as subjects responded faster overall in the Control (mean RT = 1200.17 msec) than Secondary Task condition (mean RT = 1593.02 msec). The latter finding confirms that the secondary task competed for cognitive resources with the main target classification task. A significant interaction between Task Condition and Block was also observed [$F(5,235) = 4.64$, $MSe < .001$, $p < .01$]. Although mean RTs were greater in the Secondary Task than Control condition, the difference grew smaller across trial blocks, indicating that the secondary task interfered with the main classification task less as the training session progressed.

Figure 5 shows mean RT to training items as a function of the decision strategy adopted by subjects in the test session. Mean RTs are not shown for subjects whose strategy could not be classified or those inferred to be using WADD (due to the small number of subjects using this strategy). To determine the specific effects of the Secondary Task manipulation on subjects using each of the different decision strategies, we performed a series of independent t-tests. As in Experiment 1, the ADD and Bayesian strategy groups were combined into a single compensatory strategy group. First, mean RTs for subjects using TTB-C in the Control condition did not differ from that of subjects using a compensatory strategy in the Control condition [$t(41) = 1.15$, *n.s.*]. Second, mean response time for the Secondary Task TTB-C group was significantly greater than that of the Control TTB-C group [$t(38) = 3.03$, $p < .05$]. Mean RTs did not differ between the Control compensatory and Secondary Task compensatory groups [$t(40) = 0.06$, n.s.]. Finally, mean RT was significant greater for the Secondary Task TTB-C group than the Secondary Task compensatory group [$t(37) = 2.07$, $p < .05$]. These findings indicate that the Secondary Task manipulation had a greater impact when subjects employed TTB-C than when they employed a compensatory strategy such as ADD or the Bayesian rule.

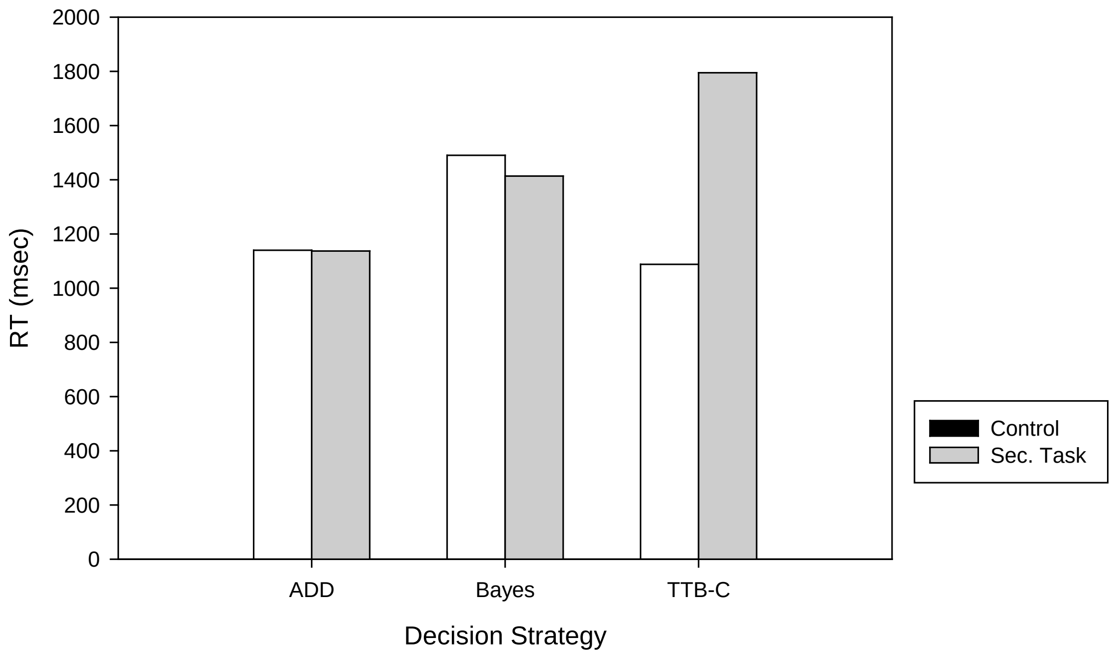

Figure 5. Mean Response Times (msec) to Training Items by Assigned Decision Strategy.

Test Session

Classification Strategy

Bröder and Schiffer's (2003a, 2003b) MLM was used to infer the decision strategy used by each subject on the basis of that subject's responses to all test items. Table 7 presents the number of subjects classified as using a given decision strategy. As can be seen, the proportions of subjects using each of the decision strategies were very similar in the Control and Secondary Task conditions and a Pearson Chi-Square test revealed no significant difference between the two conditions [$\chi2$ =2.42, df = 4, n.s.].

To assess the effect of the cue configuration of a target set, we collapsed strategy use across Task Condition and separated it according to the target set. The numbers of subjects classified as using a given strategy for each target set are shown in Table 7. As in Experiment 1, subjects tended to use TTB-C when dealing with Set 1 and the Bayesian and Additive rules when dealing with Set 2.

The critical comparison for this experiment is between the two sets in the Secondary task condition. Table 8 shows the numbers of subjects using each of the various decision procedures broken down by condition and item set. If the presence of a secondary task selectively interferes with the use of an heuristic, we would expect few subjects to employ TTB-C for either Set 1 or Set 2 in the Secondary task condition.

Table 7: Number of Subjects Classified as Using Hypothesized Decision Strategies

	Decision Procedure				
Condition	**TTB-C**	**Bayesian**	**ADD**	**WADD**	**Unclassifiable**
By Task Condition					
Control	21	12	8	2	5
Secondary task	19	14	5	1	9
By Item Set					
Set 1	32	5	4	2	5
Set 2	8	21	9	1	9

N = 48 for each presentation format & target set

Clearly, in the Secondary task condition, there is a significant difference in decision strategy usage between Set 1 and Set 2 [$\chi2 = 15.67$, df = 4, p<.05], just as in the Control condition [$\chi2 = 15.30$, df = 4, p<.05]. The pattern of decision strategies used in Set 1 did not differ between the Control and Secondary Task conditions [$\chi2 = 2.40$, df = 4, n.s.]. Thus, although the secondary task affected subjects' responses during training– slowing responses significantly when they used TTB-C – it did not affect which strategy they used in the test session. Despite the added cognitive load, subjects still tended to prefer the TTB-C heuristic for Set 1.

Table 8: Number of Subjects Classified as Using Hypothesized Decision Strategies

	Decision Procedure				
Condition	**TTB-C**	**Bayesian**	**ADD**	**WADD**	**Unclassifiable**
Control – Set 1	16	2	2	2	2
– Set 2	5	10	6	0	3
Secondary task – Set 1	16	3	2	0	3
– Set 2	3	11	3	1	6

N = 48 for each presentation format & target set

Response Time

Response times were measured after the test item disappeared from the screen from the time at which the decision prompt appeared to the time at which the subject pressed either the friend or foe key on the computer keyboard. Mean response times are shown in Table 9. Generally, subjects took about a second or less to make their responses in both Control and Secondary Task conditions.

Subjects' reaction times were not distributed normally so a transformation of all mean response times by their natural log was performed prior to analysis. Mean RT did not differ between the Control and Secondary Task conditions [$F(1,46) < 0.01$, MSe = 0.96, n.s.], which is not surprising as this factor was manipulated only during training. Although subjects in both conditions showed a tendency to respond faster to Set 2 than Set 1, this difference did not achieve statistical significance [$F(1,46) = 3.42$, $MSe = 1.77$, n.s.].

Table 9. Mean Response Times (ms) and Standard Deviations of the Mean to Test Items

		Item Type						
		All	**A**	**B**	**C**	**D**	**E**	**F**
Control								
Set 1	**Mean**	1000	1012	1073	992	930	976	1018
	SD	*537*	*462*	*522*	*503*	*508*	*450*	*477*
Set 2	**Mean**	845	845	908	764	839	802	910
	SD	*451*	*400*	*446*	*376*	*351*	*315*	*418*
Total	**Mean**	922						
	SD	*441*						
Secondary task								
Set 1	**Mean**	1083	1124	1071	1011	994	1241	1056
	SD	*537*	*503*	*566*	*545*	*481*	*588*	*553*
Set 2	**Mean**	827	816	796	759	877	920	792
	SD	*451*	*428*	*507*	*318*	*466*	*550*	*432*
Total	**Mean**	955						
	SD	*512*						

In contrast to the results of Experiment 1, subjects did show a significant effect of Item Type on RTs in the test session [$F(5,230) = 2.60$, $MSe = 0.05$, $p < .05$]. Generally, subjects responded somewhat faster for items of type C and D than all other item types. In addition, there was a significant interaction effect between Task Condition and Item Type [$F(5,230) = 3.23$, $MSe = 0.06$, $p < .05$]. Although subjects generally responded faster to items of type C and D in both task conditions, subjects exhibited some differences in RTs to other items between the Control and Secondary Task conditions. In particular, subjects were somewhat faster to items of type E than types A, B, and F in the Control condition but somewhat faster to items of type B than all others in the Secondary Task condition.

To further explore the impact of the secondary task on classification, mean response times were computed within the Control and Secondary task conditions according to the decision strategy assigned to subjects.[3] Figure 6 shows these mean response times for the ADD, Bayesian, and TTB-C strategies (means for the WADD rule are not shown because only three subjects were assigned this strategy).

[3] This analysis excluded subjects whose decision strategy could not be classified.

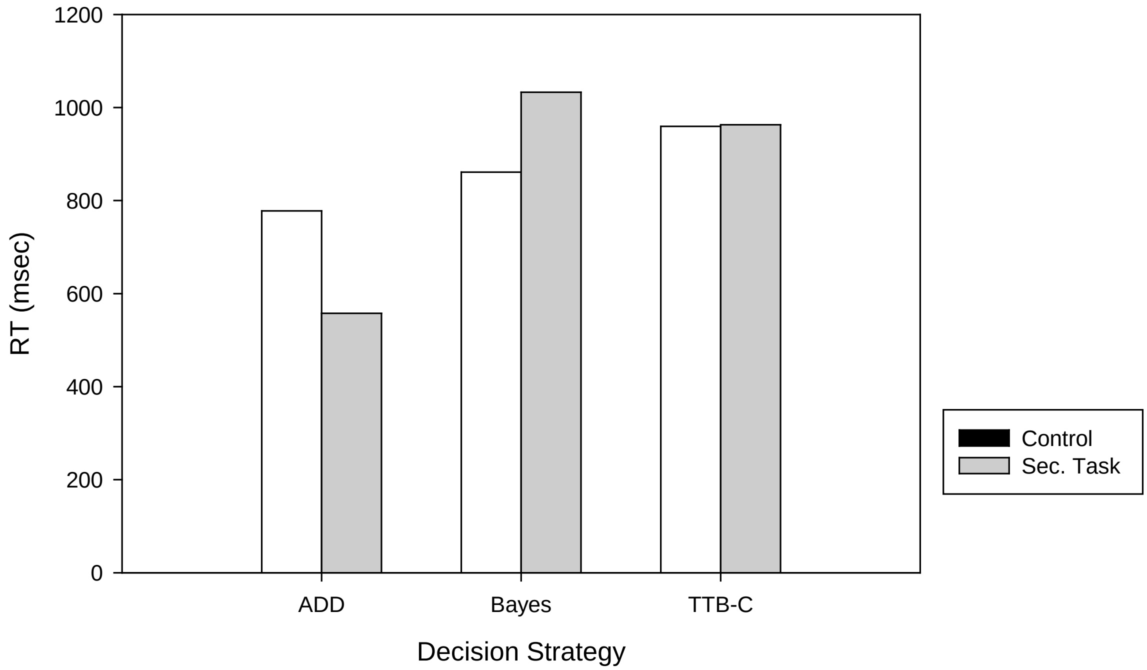

Figure 6. Mean Response Times (msec) to Test Items by Assigned Decision Strategy.

Because the secondary task manipulation was imposed during the training session only, there is no reason to expect that this factor affected RTs during the test phase.

As can be seen in Figure 6, subjects' responses were roughly the same in both the Control and Secondary Task conditions. Although subjects using ADD in the Secondary Task condition appear to have responded very quickly, it is important to remember that only four subjects were classified with this strategy in that condition. A series of independent t-tests was performed to compare mean RTs as a function of decision strategy. Mean RTs for the ADD and Bayesian strategy groups were combined into a single compensatory strategy group, as was done for RTs in the Training session. The t-tests revealed no significant differences between any of the groups; thus, subjects responded essentially as fast whether using a compensatory or heuristic decision rule in both the Control and Secondary Task conditions.

Discussion

As in Experiment 1, the secondary task did affect subjects' performance on the classification task. Subjects responded to training items more slowly when performing a simultaneous task that competed for cognitive resources, although this effect diminished somewhat over repeated training blocks. Adding a secondary task, however, did not affect subjects' selection of a decision strategy; roughly equal proportions of subjects used heuristic and compensatory strategies in both the Secondary Task and Control conditions. We had predicted that adding the secondary task during training would be more likely to affect selection of a decision strategy as it would affect subjects while they learned how to perform the classification task.

Nevertheless, subjects' selection of a decision strategy was most strongly determined by the item set with which they were interacting rather than external demands on cognitive resources.

In Experiment 1, a significant interaction effect between decision rule and task condition had been observed for decision times during the test phase. The same effect was observed in the current experiment for decision times during the training phase. Thus, again imposing the secondary task selectively interfered with performing the heuristic TTB-C strategy, suggesting that the heuristic relies on a deliberate processing system.

Conclusion

Previous experiments have demonstrated that people can employ both a fast-and-frugal heuristic and more complex additive and Bayesian strategies to classify targets as friend or foe [3][4][27]. Since both provide accurate solutions to the experimental task, it is unclear why some subjects would employ the heuristic but others the Bayesian or Additive strategies. One possible explanation is that subjects may rely on different underlying classification systems (e.g., [30]) which are conducive to different decision processes. Some researchers have suggested that people have access to two distinct cognitive systems for categorization [30][31][32]. One of these is proposed to be deliberate and suited to learning rule-based class distinctions, whereas the other is an implicit system that is automatic and suited to learning how to integrate probabilistic cues to form categories. Thus, subjects who use a fast-and-frugal heuristic may rely on a deliberate, rule-based system, whereas others who use the Bayesian or Additive rules may rely on an automatic, integrative system.

Recent evidence associates heuristics with the deliberate classification system [28]. In contrast, compensatory processes, such as the Bayesian and Additive rules, may take advantage of automatic classification. If heuristic and compensatory decision procedures are based on different cognitive systems, people may be able to advantageously switch their decision strategy to make use of whichever is better suited to the present decision making context. Using Ashby's [30][31][32] distinction between rule-based and information integration categories, for example, we might expect people to be more likely to use heuristics when they encounter the former and a compensatory strategy when they encounter the latter.

To examine the possible distinction between deliberate heuristics and automatic compensatory processes in CID judgments, we employed the dual-task method in which the impact of a secondary task on CID performance was assessed. The CID task used in these experiments is technically an information integration task because optimal performance depends on integration of all four cues. Thus, it might be expected that subjects would employ an automatic classification system, yielding judgments consistent with a Bayesian decision rule. Given the specific cue validities associated with cues, however, the maximum level of performance achievable with a heuristic such as TTB-C was almost the same as that of the Bayesian strategy. Thus, the task could be treated as a rule-based classification task with little discernable loss in accuracy. This allows subjects the option of approaching the task as either a rule-based or information-integration problem.

Based on previous findings that associate heuristics with deliberate processing and Additive or Bayesian rules with automatic processing, a competing demand on limited cognitive resources should make it more difficult to employ a heuristic, but would not greatly affect automatic associative learning potentially related to the Bayesian decision rule. The present experiment examined the effects of a secondary task while classifying contacts. We anticipated that the secondary task would make it more difficult to employ a heuristic, but would not greatly affect automatic associative learning potentially related to the Bayesian decision rules. Thus, we expected to see a larger proportion of participants using the Bayesian rule than a heuristic-based rule in a dual-task condition.

In two experiments, it was found that the proportions of participants using each of the decision strategies were very similar in the control and secondary task conditions. That is, there was no significant difference in the numbers of participants using the TTB-C versus the Bayesian or additive rules, between the control and secondary task conditions. This was true both when the secondary task was applied during the test phase and when it was applied during the training phase. Thus, subjects did not seem to be able to adjust their use of decision strategy in response to competition for cognitive resources that made a deliberate heuristic strategy less attractive.

Why did the secondary task not affect subjects' selection of a decision strategy? It may have been that the secondary task used here was not demanding enough to appreciably interfere with an heuristic strategy. Although it differentially interfered with TTB-C, this interference resulted in a slowing down of responses by only about 300 msec. Subjects may have not noticed the interfering effect of the secondary task or, if they noticed, may not have felt it was worthwhile altering their decision strategy.

Another reason we failed to observe an effect of secondary task on decision strategy selection may be that a more powerful factor determines the decision procedure a person uses. Although our hypothesis was not supported by the results in this study, it provides us with compelling evidence regarding the importance of cue salience in classification. The experiment replicated an unexpected finding of Bryant [4] that the target set studied by subjects exerted a large effect on the decision strategy employed by subjects. In this experiment, when they classified set 1, the majority of participants employed TTB-C. In contrast, with set 2, the majority of participants used the Bayesian or ADD strategies. To understand why this occurred, it is necessary to consider both the predictiveness of each cue but also the salience [4]. In set 1, the uniform was the most predictive cue but it also appears to have been the most perceptually salient cue as well. It also might have had a meaningful relationship to classification of a target as friend or foe, as subjects were familiar with the CADPAT uniforms used by (friendly) CF personnel. Participants felt it was easier to learn and accept that the CADPAT uniform as a reliable cue that the stimulus was associated with a friend classification. In set 2, the helmet was the most predictive cue but not regarded as highly salient. Subjects may not have considered the helmet as significant a feature as the uniform.

Previous research on category learning by Kruscke [39], and Nofsky et. al. [40] has suggested that cue validity is the prime determinant of a cue's use in category learning [4]. The results of the current experiment, however, suggest that the salience of a cue also plays a significant role. In set 1, the most predictive cue (uniform) was also the most perceptually salient cue, whereas in set 2, the most predictive cue was not very salient. It was suggested by Bryant [4], that when a perceptually salient cue is also the most diagnostic, participants are quickly able to notice its relation to classification and use a simple rule such as TTB-C. However, if a less salient cue is the most diagnostic, participants are likely to look at all cues, which implies the use of a compensatory or analytic decision rule [4]. In other words, TTB-C is the preferred decision rule if a salient, high validity cue exists. In contrast, if participants do not have a specific cue that stands out to them and when a non-salient cue is most predictive, they are likely to look at all cues to identify targets which suggests a compensatory and analytic decision rule.

It was suggested in a study by Martin and Caramazza [41] that categorization learning begins first when people identify cues that can distinguish category members from non-members. Each of the cues are sequentially searched and evaluated for their usefulness. In their view, the salience of cues seems to affect the order in which those cues were sampled. Perceptually salient cues are noticed early in the learning process and are subsequently incorporated in the representation of the category [4]. In other words, salient and predictive cues are more likely to be used than predictive non-salient cues and non-predictive ones. Bryant [4] suggests that people may terminate the search process in learning if they find a highly predictive cue early, which would imply the use of the TTB-C method for classification. However, if the initial cue observed was not highly predictive, the sequential search would continue until one was found. Thus, having a highly salient cue that is also predictive provides participants with the opportunity to discover the heuristic early in learning. Those participants who inspect multiple cues before discovering the most predictive one are more likely to develop a compensatory based decision strategy such as the Bayesian or Additive rules for classification.

References

1. Liebhaber, M. J., & Smith, C. A. P. (1999). *Tactical Decision-Making Under Stress: Baseline results*. Cited in Liebhaber, Kobus, & Feher (2002).
2. Cruz, E. E. (1996). *Fratricide in air-land operations*. Unpublished Master's thesis. Naval Postgraduate School, Monterey, CA.
3. Bryant, D. J. (2007). Classifying Simulated Air Threats with Fast and Frugal Heuristics. *Journal of Behavioral Decision Making, 20,* 37-64.
4. Bryant, D. J. (2009). Decision Rules for Pictorial Threat Classification. DRDC Toronto TR 2009-126, Defence R&D Canada – Toronto, Toronto, Canada.
5. Bryant, D. J., Webb, R. D. G., & McCann, C. (2003). Synthesizing two approaches to decision making in command and control. *Canadian Military Journal, Spring*, 29-34.
6. Klein, G. (1992). *Decision making in complex military environments*. Klein Associates, Fairborn, OH: Final Contract Summary Report, prepared for Naval Command, Control and Ocean Surveillance Center, San Diego, CA.
7. Yates, J. F. (1990). *Judgment and decision making*. Englewood Cliffs, NJ: Prentice Hall.
8. Hunt, E. (1994). Problem solving. In R. J. Sternberg (Ed.), *Thinking and problem solving* (pp. 215-232). San Diego, CA: Academic Press.
9. Hogarth, R. M. (1980). *Judgment and choice: The psychology of decision*. New York, NY: John Wiley.
10. Ben-Zur, H. (1998). Dimensions and patterns in decision-making models and the controlled/automatic distinction in human information processing. *European Journal of Cognitive Psychology, 10*, 171-189.
11. Fishburn, P. C. (1988). Normative theories of decision making under risk and under uncertainty. In Bell, D. E., Raiffa, H., & Tversky, A. (Eds.), *Decision making: Descriptive, normative, and prescriptive interactions* (pp. 78-98). New York, NY: Cambridge University Press.
12. Todd, P. M., & Gigerenzer, G. (2000). Precis of *simple heuristics that make us smart*. *Behavioral and Brain Sciences, 23*, 727-780.
13. Tietz, R. (1992). Semi-normative theories based on bounded rationality. *Journal of Economic Psychology, 13*, 297-314.
14. Todd, P. M. (2001). Fast and frugal heuristics for environmentally bound minds. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 51-70). Cambridge, MA: The MIT Press.
15. Sternberg, R. J. (1996). *Cognitive Psychology*. Fort Worth, TX: Harcourt Brace College Publishers.
16. Colton, R. A., & Gange, R. H. (1993). *Including the Human Element in Design of Command and Control Decision Support Systems - The KOALAS Concept*, Naval Research Lab., Washington, DC.

17. Gigerenzer, G., Todd, P. M., & The ABC Research Group (1999). *Simple heuristics that make us smart*. New York, NY: Oxford University Press.

18. Slegers, D. W., Brake, G. L., & Doherty, M. E. (2000). Probabilitic mental models with continuous predictors. *Organizational Behavior and Human Decision Processes, 81*, 98-114.

19. Gigerenzer, G., & Selten, R. (2001). Rethinking rationality. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 1-12). Cambridge, MA: The MIT Press.

20. Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review, 103*, 650-669.

21. Czerlinski, J., Gigerenzer, G., & Goldstein, D. G. (1999). How good are simple heuristics? In Gigerenzer, G., Todd, P. M., & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 97-118). New York, NY: Oxford University Press.

22. Martignon, L., & Hoffrage, U. (1999). Why does one-reason decision making work? A case study in ecological rationality. In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), *Simple heuristics that make us smart*, pp. 119-140. Oxford, UK: Oxford University Press.

23. Bröder, A. (2000). Assessing the empirical validity of the "take the best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*, 1332-1346.

24. Bröder, A., & Schiffer, S. (2003). Take the best versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General, 132*, 277-293.

25. Newell, B. R., Weston, N. J., & Shanks, D. R. (2003). Empirical tests of a fast-and-frugal heuristic: Not everyone "takes-the-best". *Organizational Behavior and Human Decision Processes, 91*, 82-96.

26. Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing "one-reason" decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29*, 53-65.

27. Bryant, D. J. (2003). *Cue validity learning in threat classification judgments*. DRDC Toronto TR 2003-041, Defence R&D Canada – Toronto, Toronto, Canada.

28. Glöckner, A., & Betsch, T. (2008). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*(5), 1055-1075.

29. Hasher, L., & Zacks, R. T. (1979). Automatic and effortful processes in memory. *Journal of Experimental Psychology: General, 108*, 356-388.

30. Waldron, E. M., & Ashby, F. G. (2001). The effects of concurrent task interference on category learning: Evidence for multiple category learning systems. *Psychonomic Bulletin & Review, 8*(1), 168-176.

31. Ashby, F. G., Maddox, W. T., & Bohil, C. J. (2002). Observational versus feedback training in rule-based and information-integration category learning. *Memory & Cognition, 30*(5), 666-677.

32. Maddox, W. T., Ashby, F. G., Ing, A. D., & Pickering, A. D. (2004). Disrupting feedback processing interferes with rule-based but not information-integration category learning. *Memory & Cognition, 32*(4), 582-591.

33. Ashby, F. G., Ell, S. W., & Waldron, E. M. (2003). Procedural learning in perceptual categorization. *Memory & Cognition, 31*(7), 1114-1125.

34. Maddox, W. T., Lauritzen, J. S., & Ing, A. D. (2007). Cognitive complexity effects in perceptual classification are dissociable. *Memory & Cognition, 35*, 885-894.

35. Zeithamova, D., & Maddox, W. T. (2006). Dual-task interference in perceptual category learning. *Memory & Cognition, 34*(2), 387-398.

36. Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), Heuristics and biases: The psychology of intuitive judgment (pp. 49-81). New York: Cambridge University Press.

37. McLeod, C. M. (1991). Half a century of research on the Stroop Effect: An integrative review. *Psychological Bulletin, 109*, 163-203.

38. Bröder, A., & Schiffer, S. (2003a). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making, 16*, 193-213.

39. Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review, 99*, 22-44.

40. Nosofsky, R. M., Palmeri, T. J., & McKinley, S. C. (1994). Rule-plus-exception model of classification learning. *Psychological Review, 101*, 53-79.

41. Martin, R. C., & Caramazza, A. (1980). Classification in well-defined and ill-defined categories: Evidence for common processing strategies. *Journal of Experimental Psychology: General, 109*, 320-353.

Annex A: Decision Procedures for Combat Identification Judgments

Given concerns that threat assessment is vulnerable to problems of information overload and uncertainty [A1], the fast and frugal heuristic approach provides a potentially useful framework in which to study time- and information-stressed decision making. Fast and frugal heuristics may be a natural means to manage a heavy information load, provided they are used in appropriate task environments. This appears to be true specifically for threat assessment, where surveys of experienced operators have indicated that operators do not consider or weigh all available data equally and that they employ decision making procedures that differ from those previously assumed [A2].

To explore the potential of fast and frugal heuristics to model human threat assessment, Bryant [4] developed a simulated air threat assessment task in which to compare predictions of different decision models. In three experiments, subjects learned to classify simulated aircraft using four probabilistic cues then classified test sets designed to contrast predictions of several compensatory and non-compensatory heuristics. Various “contacts” (simulated aircraft) were presented on a simulated radar screen for subjects to classify as either friend or foe based on the values of four cues. Each cue value had a specific probability of being associated with friend and foe contacts, with these probabilities determining the cue’s validity in classifying contacts.

To apply the fast and frugal heuristic approach to threat assessment, Bryant [A3] [A4] devised decision procedures specifically for the threat classification task. The following sections describe these in detail.

Compensatory Rules

Just as TTB-C is an adaptation of the TTB heuristic to the single-choice classification problem, other two-alternative choice decision strategies can be adapted. Among the decision strategies that have been examined are Franklin’s Rule and Dawes’ Rule. Franklin’s rule is a procedure by which a decision maker calculates the sum of cue values weighted by the corresponding cue validities for each alternative and selects the alternative with the highest score [A5]. Dawes’ rule is similar and calculates the sum of unweighted cue values and selects the alternative with the highest score. Because both Franklin’s and Dawes’ Rules add bits of evidence for an alternative, they can be termed Additive Rules (for the sake of clarity, these rules will be referred to as the Weighted Additive and Unweighted Additive rules). Both are compensatory, meaning that they employ all available cues although they do not compute probabilities to reach a decision.

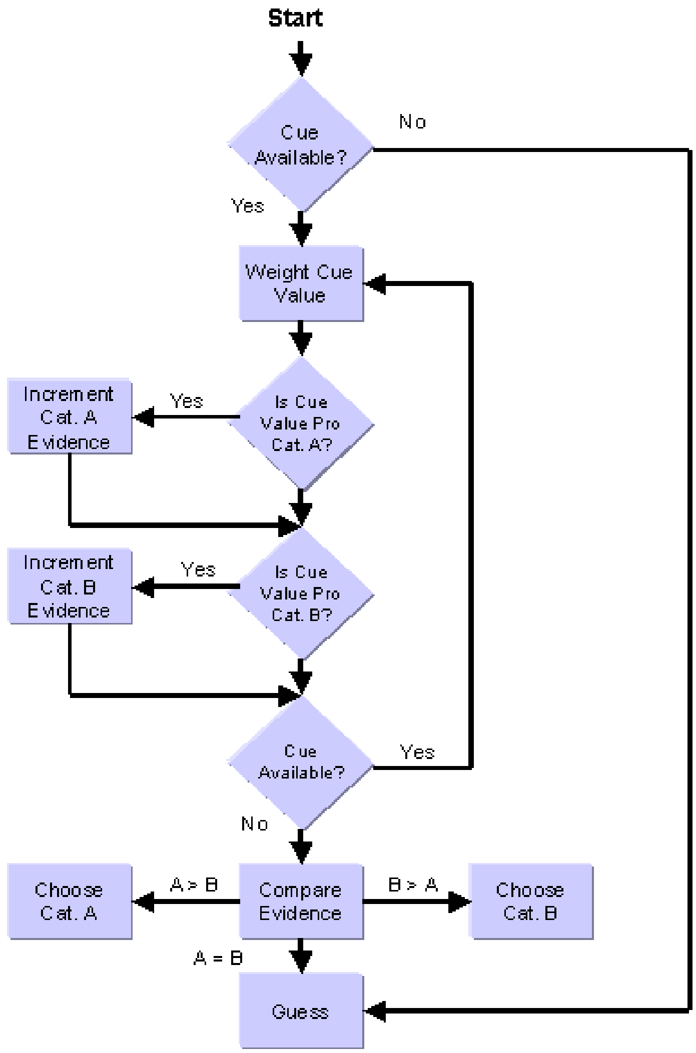

Figure A1: Weighted Version of the Additive Rule for Classification

Versions of the Additive Rules were formulated for the threat classification task. Unlike their progenitors, they do not compare cue values for two alternatives but rather examine each cue value and assign evidence toward either friend or foe classification, depending on the associations of cue values to threat class. A running sum is maintained and, after all available cues have been inspected, used to place the contact in the friend or foe category. Figure A1 contains an illustration of Weighted Additive (WADD) Rule, which weights cues by their validity, adapted for threat classification. A classification version of the Unweighted Additive Rule (ADD) is performed just as illustrated in Figure A1 but without the weighting step following the selection of a cue. These rules use more information than TTB-C but are more generally useful because their accuracy is not limited to cases where a single cue is highly predictive.

Bayesian Procedures

Another way to make a judgment on the basis of probabilistic cues is by means of a “naïve” Bayesian classifier. A naïve Bayes classifier is a system for making probabilistic inference based on applying Bayes' theorem with a strong (i.e. naïve) assumption of independence among cues. That is, it assumes that the presence of any particular cue is unrelated to the presence of any other cue. In this procedure, a class of object is represented by a base rate (overall probability of an instance of that class occurring) and set of conditional probabilities that specify relationships of attributes to that class. Despite their simplifying assumption, naïve Bayes classifiers often work very well in complex real-world situations. Depending on the precise nature of the probability model, naïve Bayes classifiers can be trained very efficiently in a supervised learning setting. Thus, it is an appropriate model for learning the friend/foe classification used in Bryant [A4].

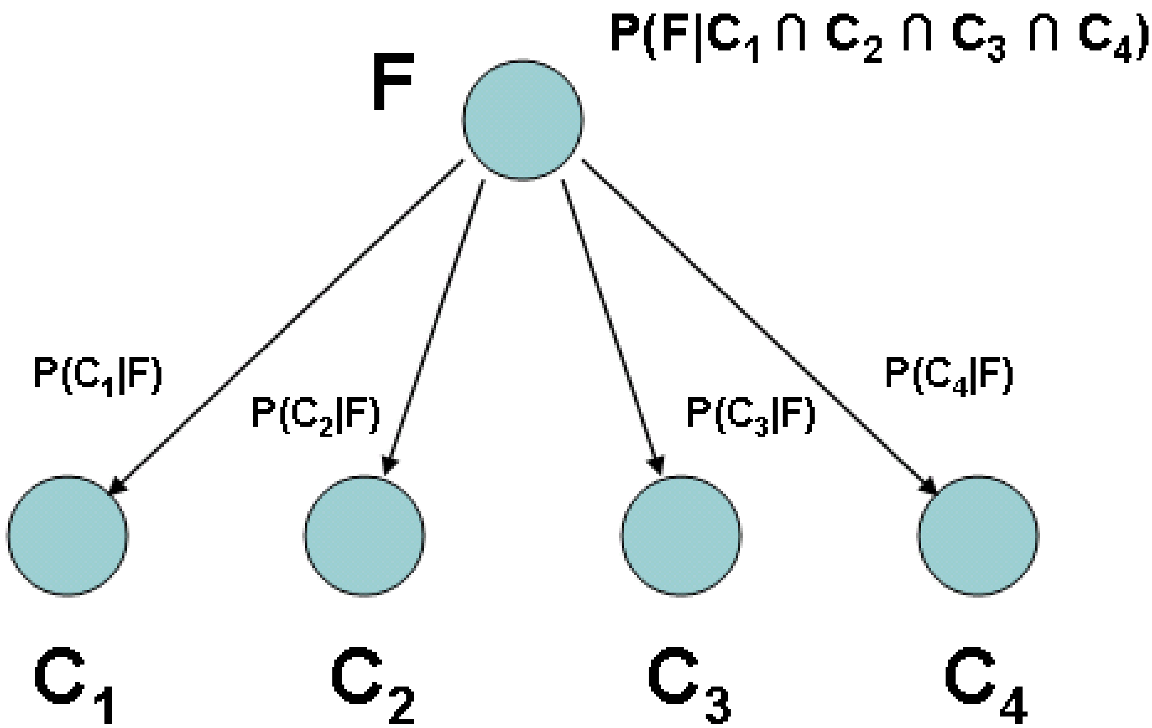

Figure A2. A Bayesian Network representation of the task used by Bryant [4]

A Bayesian classifier can be instantiated by a number of different algorithms that calculate conditional probabilities. It can also be instantiated in a Bayesian network (or a belief network), which is a probabilistic graphical model that represents a set of variables and their probabilistic independencies. Thus, a Bayesian network can represent the probabilistic relationships between threat class (friend or foe) and predictive cues. Given a set of cues, the network can be used to compute the probabilities of the target being a friend or a foe.

A Bayesian network for the friend/foe task is shown in Figure A2. The top node represents the classification of a target as a friend (F). The case of a foe would be represented by the negation of friend ($\overline{F}$). Four nodes representing characteristics of the target, or cues ($C_{1\text{-}4}$), are connected to it according to their probabilistic association to the class of the target. Thus, each line linking a cue to the classification node is labeled by the conditional probability of the cue occurring given the classification of friend. Considering all cues as a set, the classification node represents the conditional probability of that class being true given the presence of the four linked cues. This is given by the formula (1):

$$P(F \mid C_1 \cap C_2 \cap C_3 \cap C_4) = \frac{P(C_1 \mid F) \bullet P(C_2 \mid F) \bullet P(C_3 \mid F) \bullet P(C_4 \mid F)}{\left[P(C_1 \mid F) \bullet P(C_2 \mid F) \bullet P(C_3 \mid F) \bullet P(C_4 \mid F) + P(C_1 \mid \overline{F}) \bullet P(C_2 \mid \overline{F}) \bullet P(C_3 \mid \overline{F}) \bullet P(C_4 \mid \overline{F})\right]} \tag{1}$$

Where:

$P(C_j \mid \overline{F}) = 1 - P(C_j \mid F)$, j = 1 to 4.

The Bayesian strategy was assumed to compute the conditional probabilities of friend and foe classifications given the particular pattern of cue values for a contact and select the alternative with the higher probability of being the correct classification. This is formally equivalent to the “profile memorization method,” which memorizes which option has the greater conditional probability of being correct for each cue configuration [A6]. Martignon and Hoffrage [A7] have described this method as the optimal Bayesian method for fitting known data.

The Take-the-Best-for-Classification Heuristic

A variant of TTB, called Take-the-Best-for-Classification heuristic (TTB-C), was devised to perform the threat classification task.[4] Illustrated in Figure A3, TTB-C is based on the premise that the single most valid cue can be used to make accurate threat classification judgments in a task environment in which that cue is highly predictive. Unlike TTB, which chooses between two objects along a single dimension, TTB-C places a single object into one of two categories. Thus, TTB-C is simpler in some respects than TTB but it takes from TTB the basic search concept of locating the single best cue to make its decision.

Given an as-yet-unclassified contact, TTB-C begins by searching for the single most valid cue to serve as the basis for classification. In the experiment described in this report, all cues associated with contacts will be available, so the most valid cue should always be inspected. When the most valid available cue is located, the heuristic assesses which threat class has the greater probability of being true given the value of that cue and makes that threat class the output of the heuristic. The heuristic will be applied here to an experimental task in which subjects make a simplified two-category choice (friend or foe) but the heuristic could apply to threat classification with a larger set of threat classes. With the contact classified, the heuristic terminates. Should no valid cue be found, the heuristic can only guess.

TTB-C, as illustrated here, assumes that there exist one or more cues that have some non-random association to the threat class of contacts and that all, or some subset, of these cues can be inspected by the decision maker. Moreover, the decision maker must have acquired,

[4] TTB-C is also derivable from the Lexicographic heuristic for two-alternative choice, which is a generalization of Take-the-Best.

through experience or training, knowledge of the relative validities of these cues. These, of course, are not minor assumptions but there is sufficient evidence that people can learn cue validities, even if their learning is imperfect [A8] [A9].

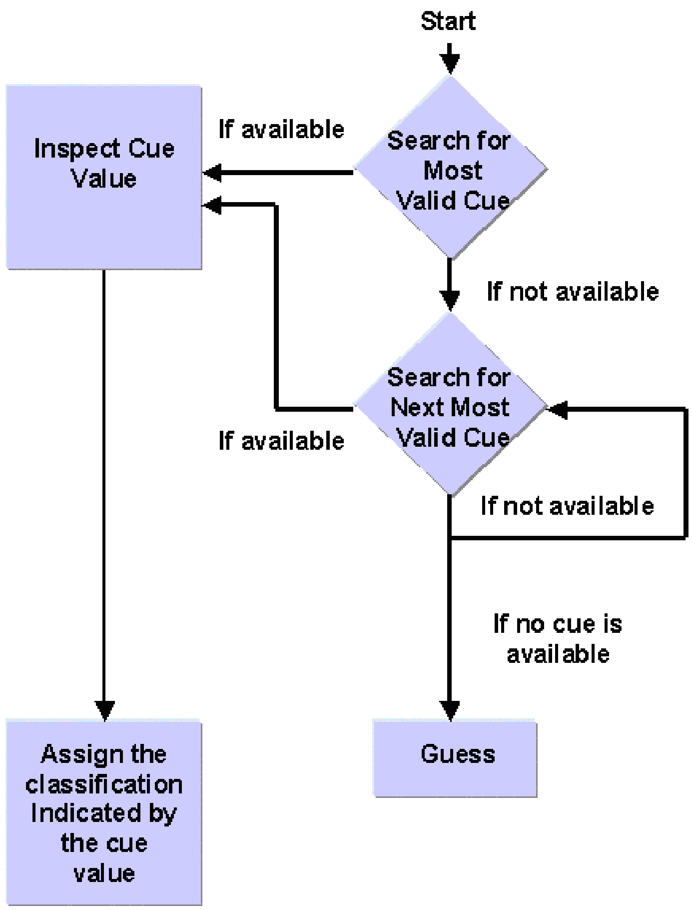

Figure A3. The Take-the-Best-for-Classification (TTB-C) Heuristic

References

A1. Liebhaber, M. J., & Smith, C. A. P. (1999). *Tactical decision-making under stress: Baseline results*. Cited in Liebhaber, Kobus, & Feher (2002).

A2. Liebhaber, M. J., Kobus, D. A., & Feher, B. A. (2002). *Studies of U.S. Navy air defense threat assessment: Cues, information order, and impact of conflicting data*. Technical Report 1888. SPAWAR Systems Center, San Diego, CA.

A3. Bryant, D. J. (2003). *Cue validity learning in threat classification judgments*. DRDC Toronto TR 2003-041, Defence R&D Canada – Toronto, Toronto, Canada.

A4. Bryant, D. J. (2007). Classifying simulated air threats with Fast and Frugal Heuristics. *Journal of Behavioral Decision Making, 20*, 37-64.

A5. Reiskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 141-167). Oxford, UK: Oxford University Press.

A6. Gigerenzer, G., Todd, P. M., & The ABC Research Group (1999). *Simple heuristics that make us smart*. New York, NY: Oxford University Press.

A7. Martignon, L., & Hoffrage, U. (1999). Why does one-reason decision making work? A case study in ecological rationality. In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 119-140). Oxford, UK: Oxford University Press.

A8. Brehmer, B. (1973). Single-cue probability learning as a function of the sign and magnitude of the correlation between cue and criterion. *Organizational Behavior and Human Decision Processes, 9*, 377-395.

A9. Himmelfarb, S. (1970). Effects of cue validity differences in weighting information. *Journal of Mathematical Psychology, 7*, 531-539.

Annex B: Maximum Likelihood Method

The Maximum Likelihood Method (MLM) method was developed by Bröder and Schiffer [B1][B2] as a means to assess which of a potential set of decision strategies was most likely employed by a subject in a multiple cue-based decision task. In short, the method they developed determines the conditional probability that a subject's sequence of responses for multiple decisions would occur given the use of a specified decision strategy. By determining this probability for a set of strategies, one is able to identify the most likely strategy to have produced the subject's observed responses.

The MLM is applied to a decision task in which items belonged to one of two possible types (friend or foe) and were described by values along four binary cues. The validity of each cue as a predictor of item type is a variable. For the purpose of illustrating the MLM, consider the cues presented in Table B1 along with the validity of each as a predictor of friend or foe.

Table B1. Relative Frequencies of Cue Values for Friend and Foe Contacts

	SET 1							
	Cue 1 (Cockpit)		***Cue 2 (Nose)***		***Cue 3 (Wing)***		***Cue 4 (Tail)***	
	Value 3 (extended)	***Value 1 (Bubble)***	***Value 3 (Round)***	***Value 1 (Cone)***	***Value 3 (Swept)***	***Value 1 (Delta)***	***Value 3 (Flexed)***	***Value 1 (Raised)***
Friend	90%	10%	60%	40%	30%	70%	20%	80%
Foe	10%	90%	40%	60%	70%	30%	80%	20%
	SET 2							
	Cue 1 (Nose)		***Cue 2 (Tail)***		***Cue 3 (Cockpit)***		***Cue 4 (Wing)***	
	Value 3 (Round)	***Value 1 (Cone)***	***Value 3 (Flexed)***	***Value 1 (Raised)***	***Value 3 (extended)***	***Value 1 (Bubble)***	***Value 3 (Swept)***	***Value 1 (Delta)***
Friend	90%	10%	60%	40%	30%	70%	20%	80%
Foe	10%	90%	40%	60%	70%	30%	80%	20%

Given four binary cues, there are 16 possible cue configurations that can be associated with friend or foe. All decision strategies under consideration make the same predictions for some of these configurations. That is, there are cue configurations for which each strategy will predict friend or foe. There are, however, a subset of items that elicit different predictions from at least two strategies. Bröder and Schiffer's MLM makes use of these items. In particular, there are three critical item types j (j = 1, 2, or 3) for the purpose of assessing decision strategy, which are listed in Table B2. Type 1 items elicit a prediction from the

TTB-C strategy that is different from all others (types 1a and 1b simply reflect different cue configurations in which TTB-C makes a prediction opposite from the other strategies). Type 2 items elicit the same predictions from TTB-C and a Bayesian strategy but cannot be solved by either the Weighted or Unweighted Additive Rules, which can only guess. Type 3 items elicit the same predictions from TTB-C, the Bayesian strategy, and the Weighted Additive Rule but elicit guessing from the Unweighted Additive Rule.

Table B2: Examples of Different Types of Items Used to Assess Decision Strategies

	Item Type					
	1		**2**		**3**	
Attribute/ Strategy	**1a**	**1b**	**2a**	**2b**	**3a**	**3b**
Cockpit	Extended	Bubble	Extended	Bubble	Extended	Bubble
Nose	Cone	Round	Round	Cone	Cone	Round
Wing	Swept	Delta	Swept	Delta	Swept	Delta
Tail	Flexed	Raised	Flexed	Raised	Raised	Flexed
Prediction of Strategies						
TTB-C	Friend	Foe	Friend	Foe	Friend	Foe
Bayesian	Foe	Friend	Friend	Foe	Friend	Foe
Unweighted Additive	Foe	Friend	Guess	Guess	Guess	Guess
Weighted Prose	Foe	Friend	Guess	Guess	Friend	Foe

The method determines the decision procedure that has the greatest likelihood of producing the data based on the predictions of the candidate set of procedures under consideration. In the experiments described in this report, those procedures are TTB-C, Bayesian, WADD, ADD, and Guessing. The method makes the assumption that subjects generate responses to test items according to one of these procedures is. It also assumes that subjects have a certain probability, ε, of making an error and generating a response not predicted by the procedure being used.

The likelihood of a subject's observed data vector (i.e. sequence of responses to test items) is calculated by the following formula:

$$L(n_{jk}, n_{jk}^{\varepsilon} \mid k, \varepsilon_k, n_j) = \prod_{j=1}^{3} \binom{n_j}{n_{jk}} \times (1-\varepsilon_k)^{n_{jk}} \times_{\varepsilon}^{(n_j - n_{jk})}$$

(A1)

Where,

n_j = number of items of each type *j* presented in an experiment,

n_{jk} = number of choices in item type *j* that were predicted by strategy *k*,

n^{ε}_{jk} = number of choices in item type *j* not predicted by strategy *k*, such that $n^{\varepsilon}_{jk} + n_{jk} = 1$,

ε_k = error probability of choosing the option not conforming to strategy *k*.

Thus, equation A1 gives the likelihood $L(n_{jk}, n_{jk}^{\varepsilon} \mid k, \varepsilon_k, n_j)$ that the observed data vector **n** is equal to $(n_{jk}, n_{jk}^{\varepsilon})$, given strategy *k*, and unknown error probability ε_k. The unknown error term can be estimated by fitting the corresponding joint multinomial model to the frequency data (Hu & Batchelder, 1994), or by applying the formula given in Equation A2:

$$\hat{\varepsilon} = \frac{\sum_{j=1}^{3} n_{jk}^{\varepsilon}}{\sum_{j=1}^{3} n_j}$$

(A2)

The following adjustments are applied to these formulae. When k = WADD, the index j in Equation A2 only runs from 1 to 2 because a person using WADD must guess for item type 2 and $\varepsilon_k = 0.5$ in Equation A1 for the case *k* = WADD and *j* = 2. When k = ADD, the index j in Equation A2 only runs from 1 to 1 because a person using ADD must guess for item types 2 and 3 and $\varepsilon_k = 0.5$ in Equation A1 for the cases *k* = ADD and *j* = 2 and *k* = ADD and *j* = 3. For *k* = Guessing, no parameter estimation is necessary and all error probabilities are set to 0.5 in Equation A1.

To classify a subject's decision strategy, a likelihood ratio (Equation A1) is computed for every strategy and the vector classified as being produced by the particular strategy if the likelihood ration in favour of this strategy is larger than 1. Otherwise, the vector remains unclassified.

The power of MLM to discriminate between strategies depends on the numbers of discriminating items that do not yield guessing responses from one or more decision strategy. Thus, discriminating the WADD and ADD strategies may be more difficult than discriminating the TTB-C and Bayesian strategies. Because the Guessing model has no free parameter, the other models will fit better than the random model in almost all cases.

References

B1. Bröder, A., & Schiffer, S. (2003). Take the best versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General*, *132*, 277-293.

B2. Bröder, A., & Schiffer, S. (2003). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making, 16*, 193-213.

List of symbols/abbreviations/acronyms/initialisms

ADD	Unweighted Additive Rule
ANOVA	Analysis of Variance
CID	Combat Identification
DRDC	Defence Research & Development Canada
HREC	Human Research Ethics Committee
IFF	Interrogate-Friend-Foe
MLM	Maximum Likelihood Method
MSe	Mean Square Error
PC	Personal Computer
TTB	Take-the-Best
TTB-C	Take-the-Best-for-Classification
WADD	Weighted Additive Rule

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(U) Two experiments used a dual task method to investigate whether compensatory and heuristic decision rules are based on distinct computational systems. Subjects learned to classify pictures of soldiers as friend or foe through trial−and−error learning then completed a test session designed to allow inference of subjects' decision strategies. In both experiments, subjects completed a condition in which they performed a simultaneous secondary task designed to consume executive working memory capacity [35], either at the time of test (Experiment 1) or during the training session (Experiment 2). In both cases, subjects exhibited slower responses when performing the secondary task than in a control condition, indicating that the secondary task competed for cognitive resources. The presence of the secondary task, however, produced significantly slower responses for those subjects classified as using a simple heuristic as opposed to a more complex compensatory strategy, which is consistent with research linking heuristics to a deliberate classification system and compensatory strategies to an automatic system. The secondary task manipulation, however, did not affect the proportions of subjects using the heuristic and compensatory decision rules. The results of two experiments suggest that heuristic and compensatory decision rules are mediated by different classification systems. The presence of competing cognitive demands, however, does not seem to affect whether a subject uses an heuristic or compensatory strategy.

(U) Deux expériences ont utilisé une méthode à double tâche pour étudier si des règles de décision compensatoires et heuristiques sont fondées sur des systèmes de calcul distincts. Les sujets ont appris à classer des photos de soldats en tant qu'amis ou ennemis par apprentissage par essai et par erreur et ont alors subi une séance de tests conçus pour permettre l'inférence des décisions sur les stratégies des sujets. Dans les deux expériences, les sujets étaient dans une situation dans laquelle ils exécutaient simultanément une tâche secondaire conçue pour utiliser la capacité de mémoire de travail exécutive [35], soit au moment du test (Expérience no 1) soit pendant la séance de formation (Expérience no 2). Dans les deux cas, les sujets ont réagi plus lentement lorsqu'ils exécutaient une tâche secondaire que dans une situation contrôlée, ce qui indique que la tâche secondaire était en compétition pour des ressources cognitives. La présence de la tâche secondaire toutefois, a entraîné des réponses considérablement plus lentes pour les sujets classés comme utilisant une stratégie heuristique simple en opposition à une stratégie compensatoire plus complexe, ce qui est conforme avec la recherche liant la stratégie heuristique à un système de classification délibéré et les stratégies compensatoires à un système automatique. La manipulation de la tâche secondaire, toutefois, n'a pas affecté les proportions de sujets utilisant des règles de décision heuristiques et compensatoires. Les résultats des deux expériences suggèrent que les règles de prise de décision heuristiques et compensatoires sont soumises à différents systèmes de classification. La présence d'exigences cognitives concurrentes, toutefois, ne semble pas affecter l'utilisation ou non par un sujet d'une stratégie heuristique ou compensatoire.

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(U) combat identification, classification, heuristic

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