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Strategy Constancy Amidst Implementation Differences: Interaction-Intensive Versus Memory-Intensive Adaptations To Information Access In Decision-Making

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Abstract

Over the last two decades attempts to quantify decision-making have established that, under a wide range of conditions, people trade-off effectiveness for efficiency in the strategies they adopt. However, as interesting, significant, and influential as this research has been, its scope is limited by three factors; the coarseness of how effort was measured, the confounding of the costs of steps in the decision-making algorithm with the costs of steps in a given task environment, and the static nature of the decision tasks studied. In the current study, we embedded a decision-making task in a dynamic task environment and varied the cost required for the information access step. Across three conditions, small changes in the cost of interactive behavior led to changes in the strategy adopted for decision-making as well as to differences in how a step in the same strategy was implemented.

Introduction

In the 80's and 90's, Payne, Bettman, and Johnson (1993) showed that decision-makers trade-off efficiency of their decision making strategy for the effort it requires. They attempted to quantify the cognitive effort of decision making by counting the number of steps that different strategies required for the same decision. The conclusion of this work was that people adapt to a wide variety of conditions to find a strategy that is about as accurate as it needs to be for as little cognitive effort as possible.

As interesting, significant, and influential as Payne, et al.'s work was, its scope was limited by three factors; the coarseness of how effort was measured, the confounding of the costs of steps in the decision-making algorithm with the costs of steps in a given task environment, and the static nature of the decision tasks studied.

First, the *elementary information processes* (EIPs) that Payne et al. used to count steps were neither elementary or steps. By today's standards EIPs such as "reading value, comparing two values or storing a result in long-term memory" (Todd & Benbasat, 2000) would be analyzed as a series of more fundamental cognitive, perceptual, and action operations. Furthermore, the count of steps was not based on an analysis of the decision-making process executed by a human, but stemmed from task analyses of the minimum number of steps a perfect agent would require to execute the algorithm. The step count did not consider the mis-steps or re-steps taken by a boundedly rational agent as they skipped a step or forgot an intermediary product, and then backed up and redid a number of steps to recover.

Second is the confounding of the costs of a step in the decision-making algorithm with the costs associated with how a step is implemented in a given task environment. Research has shown that the organization, form, and sequence of information influences strategy selection (for example, Fennema & Kleinmuntz, 1995; Kleinmuntz & Schkade, 1993; Schkade & Kleinmuntz, 1994). Other research has looked at how individual differences in working memory capacity interact with interface design to affect performance on decision-making tasks (Lohse, 1997). Other studies have looked at how the design of decision aids may have unintended consequences for the decision strategies that people adopt (Adelman, Miller, & Yeo, 2001; Benbasat & Todd, 1996; Rose & Wolfe, 2000; Todd & Benbasat, 1994, 1999, 2000). At least one study has investigated how the cost of information access affects strategy selection (Lohse & Johnson, 1996).

The third limit on the scope of Payne, et al.'s pioneering work is that the decision-making tasks they used were static, not dynamic. Although time constraints were sometimes introduced (Payne, Bettman, & Luce, 1996), these were extrinsic, not intrinsic to the decision-making task. For example, subjects were told to work quickly, timed, or rewarded for fast performance. Such extrinsic time pressure differs from tasks where the information, options, and criteria for decision-making change over time (Adelman, Bresnick, Black, Marvin, & Sak, 1996) or in which an early step in decision-making may result in changes to the task environment (Ehret, Gray, & Kirschenbaum, 2000). Hastie (2001) has characterized these dynamic situations as entailing a series of "linked decisions in a dynamic, temporally extended future" and has marked understanding this type of decision making as one of his 16 challenges for decision-making research in the 21st century.

The current paper reports empirical data from the first of a planned series of experimental and modeling efforts to extend the scope of decision-making research. In the study reported here, decision-making was embedded as an integral part of a dynamic classification task. Subjects' goal was to score as high as possible on the classification task while maximizing performance on the decision-making task. This initial study focuses on the ways in which varying the cost of interactive behavior affects the decision-making process. Specifically, across three between-subject conditions, we introduced modest differences in the cost of information access and studied how these differences affected the mix of cognitive, perceptual, and action operations for acquiring and comparing information.

Method

Subjects

Forty undergraduate students participated for approximately five hours each. Seven failed to complete the study. Subjects were either given course credit or were paid $5.00 per hour of participation and a $5.00 per hour completion bonus. Subjects were run individually.

Task

The experimental task was a preferential choice decision-making task embedded in the Argus Prime simulated radar-operator task environment (Schoelles & Gray, 2001a). Argus Prime is a complex but tractable simulated task environment (Gray, 2002) that we have used in a variety of studies (see, e.g., Gray & Schoelles, 2003; Schoelles, 2002; Schoelles & Gray, 2001b).

Classification Task. For the classification task, the subject must assess the threat value of each target in each sector of a radar screen (depicted in Figure 1). The screen represents an airborne radar console with ownship at the bottom. Arcs divide the screen into four sectors; each sector is fifty miles wide. The task is dynamic since the targets have a speed and course. A session is scenario driven; that is, the initial time of appearance, range, bearing, course, speed, and altitude of each target are read from an experimenter-generated file. The scenario can contain events that change a target's speed, course, or altitude. New targets can appear at any time during the scenario.

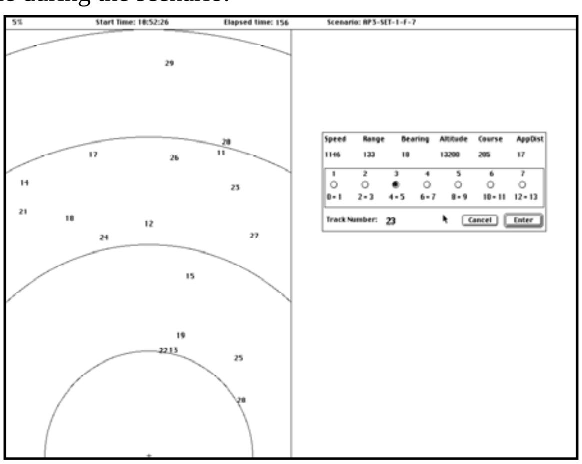

Figure 1: Argus Prime Radar Screen (left) and Information/Decision Window (upper right).

The subject selects (i.e., hooks) a target by moving the cursor to its icon (i.e., track number) and clicking. When a target has been hooked, an information window appears (on the upper-right of the display) that contains the track number of the target hooked and the current value of target attributes such as speed, bearing, altitude, and course. The subject's task is to combine these values, using an algorithm that we have taught them, and to map the result onto a 7–point threat value scale (at the bottom of the information window).

Targets must be classified once for each sector that they enter. If a target leaves a sector before the subject can classify it, it is considered incorrectly classified and a score of zero is assigned. A running score that indicates percentage of targets correctly classified is shown in the upper-left of the display. For this study, each Argus Prime scenario lasted 12-min. During this period a subject had the opportunity to calculate the threat value of between 70 and 90 targets.

The Decision–Making Task (DMT). The decision-making task (DMT) was added to Argus Prime for this study. As discussed in the Procedure section, subjects were introduced to the DMT after an hour of training and a second hour of practice on the classification task.

Each scenario proceeded until the subject had classified 8 targets. At this point, a DMT presented the subject with 4 or 6 targets for which he or she had already calculated the threat value. All groups were given the identification number for each of the DMT alternatives in a *target-column* that appeared in the lower right of the display (this area is blank in Figure 1). The subject's task was to determine which target had the highest threat value and select that target by clicking on its number in the target-column. The DMT ended and the classification task resumed when the subject clicked the CHOOSE button located below the target-column.

On making a correct choice, feedback was given via a simulated explosion, the chosen aircraft was removed from the radar screen, and the overall percent score for decision-making on that scenario was increased. If the participant chose the incorrect target, the participant's overall percent score for that scenario was reduced. A running average of DMT performance was presented to the right of the classification score. After classifying or re-classifying 8 more aircraft, another DMT was presented. This sequence continued until the end of each scenario.

Procedure

Subjects were randomly assigned to one of three DMT conditions: Table, 0-Second Lockout (0-Lock), or 2-Second Lockout (2-Lock). We were most interested in differences between the two lockout conditions, with the Table condition providing a measure of how high decision-making performance could be in this task environment under near optimal conditions.

As in other Argus Prime studies, subjects were trained for 1-hr on the Argus Prime classification task. They then practiced this task during their second hour by performing four scenarios in which the classification task was the only task. After the fourth scenario, subjects were given a short break and were then instructed on the DMT task. Training on the DMT took approximately 10-min. During the last 8 scenarios (5 through 12), subjects continued doing the classification task while being interrupted to perform the DMT.

The more time spent on the DMT, the more likely it would be that a target would cross a sector boundary without being classified. Such unclassified targets were assigned a score of zero. Hence, time on the DMT decreased time available for classification. This, in turn, placed pressure on the subjects to perform the DMT quickly.

The three between-subject conditions differed in their cost of information access. As it was unclear to us how demanding the DMT would be in the Argus Prime task environment, the Table condition provided near minimum access costs. For this condition the numeric threat value for each target was listed in the target-column next to the target's identification number. Subjects simply scanned the target-column for the highest threat value (a 1–7 scale).

In contrast, to obtain a threat value, the 0-Lock and 2-Lock groups had to locate the target on the radar screen and move the cursor to it. Similar to a "tool-tip", the threat value then appeared next to the target. For 0-Lock, the threat value appeared as soon as the cursor moved to the target. For 2-Lock, the threat value appeared after a 2-s delay.

Results

Our focus is on process measures; namely, how the cost of information access affects the combination of cognitive, perceptual, and action operators required to implement the information access step in decision-making. For these comparisons, we focus on the two lockout conditions as we have not yet analyzed the eye movement data required to infer process in the Table condition. However, before discussing the process measures we look at outcome measures for both classification and decision-making. For these outcome measures, the Table condition provides a baseline against which to compare the effect of increased access costs on outcome.

Classification

All subjects received four practice scenarios of Argus Prime with the classification task only, followed by 8 scenarios where performance on the classification task was interrupted by the decision-making task.

An analysis of variance (ANOVA) that looked at classification performance over blocks of scenarios (scenarios 1–4, 5–8, and 9–12) yielded a significant main effect of block, F (2, 30) = 3.1, p = 0.0597, MSE = 2313. Performance improved from a mean of 56% during practice to 66% in the first four DMT scenarios to 72% in the final four DMT scenarios (see Figure 2).

All conditions were treated the same through the initial training and initial four practice scenarios. Hence, performance on the four practice scenarios provides an opportunity to determine whether the subjects in the three conditions were of roughly equal ability (as per the assumption of random assignment of subjects to condition). A second ANOVA was conducted on scenarios 1–4. As judged by the classification scores there were no differences among the three groups (F < 1). Any difference in classification performance during the 8 DMT scenarios will be regarded as due to the DMT manipulation.

A third ANOVA focused on classification performance during the 8 DMT scenarios (scenarios 5 through 12). Classification scores varied significantly between conditions [F (2, 30) = 7.0, p = 0.003, MSE = 3118.9], Table = 79%, 0-Lock = 64%, and 2-Lock = 65%. Planned comparisons showed that this difference was localized in the Table versus 0- and 2-Lock comparison (p = .0008) with no difference between 0-Lock and 2-Lock (F < 1). Performance increased from scenario 5–8 to 9–12 [F (1, 30) = 33.6, p = .0001, MSE = 1167] but this effect did not interact with DMT condition (p = 0.12).

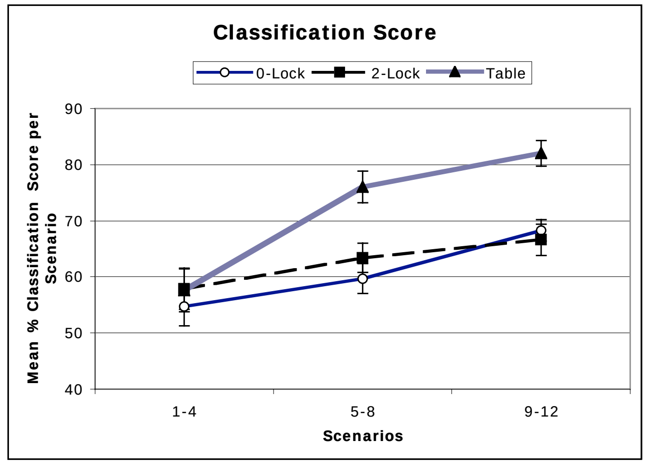

Figure 2: Classification Score across Practice scenarios (1–4) and DMT scenarios (5–8 and 9–12). (Error bars show the standard error.)

Summary of Classification Performance. The three groups were equal in their classification performance during practice (scenarios 1–4) and each continued to improve through the first and then second set of DMT scenarios (5–8 and 9–12). However, once the DMT began, the two lockout conditions performed lower on the classification task than the Table condition. As discussed below, the Table condition spent much less time on the DMT than did the lockout conditions. Hence, we believe the difference in classification performance is simply attributable to the difference in time spent by the three groups on the classification task.

Decision-Making Task (DMT)

Outcome Measures. Although performance on the decision-making task was uniformly high (see Figure 3), there was a significant difference between conditions [F (2, 30) = 10.4, p = .0004, MSE = 0.05] with Table being almost perfect (0.98) followed by 0-Lock (0.94) and then by 2-Lock (0.91). Planned comparisons showed the difference between Table and the two lockout conditions to be significant (p = .0003) and the difference between 0-Lock versus 2-Lock to be marginally significant (p = .064). The influence of number of choices (DMT-4 versus DMT-6) was also significant [F (1, 20) = 14.25, p = .0007, MSE = .043]. The interaction of number of choices with condition was marginally significant, F (2, 20) = 2.71, p = .08, MSE = .008.

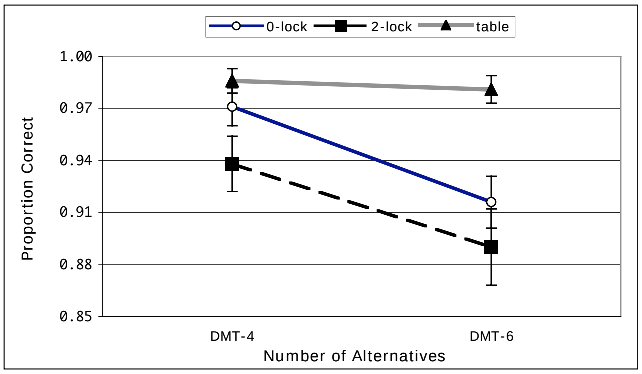

Figure 3: Proportion Correct Choices in Decision Making Task by Number of Alternatives (DMT-4 and DMT-6) and Interface Condition. (Error bars show the standard error.)

A second outcome measure is the time per DMT. This measure yields a significant effect of condition [F (2, 30) = 27.45, p = .0001, MSE = 4953] with Table spending a mere 2.7-s per DMT, 0-Lock spending 16.5-s and 2-Lock spending 23.6-s per DMT. The effect of number of targets per DMT was significant (p = .0005); however, this effect is constrained by a significant interaction of condition by DMT number [F (2, 30) = 3.21, p = 0.054, MSE = 83.8]. This interaction reflects the near asymptotic performance of Table in both DMT-4 (2.6-s) and DMT-6 (2.7-s) whereas both of the Lock groups showed a healthy increase in time from DMT-4 to DMT-6 (14.2 to 18.8 for 0-Lock and 20.8 to 26.3 for 2-Lock).

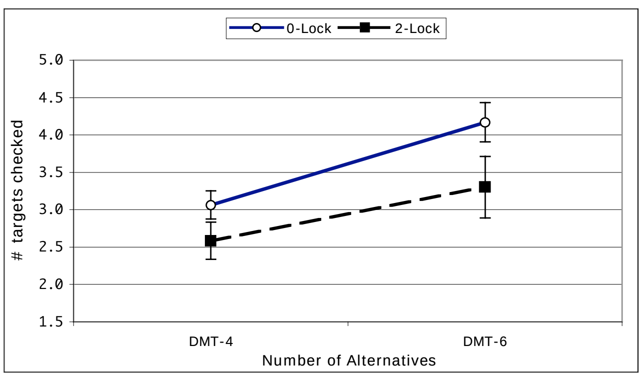

Figure 4: Number of different targets checked per DMT for 0-Lock and 2-Lock. (Error bars show the standard error.)

Of course the 2-Lock condition was locked out for 2-s for each check they made. To determine the contribution of lockout time to the difference between 0-Lock and 2-Lock we subtracted 2-s for each check or recheck made by 2-Lock. With this adjustment, time per 0-Lock versus 2-Lock was no longer significant (F < 1), leaving only a significant main effect of DMT target number [F (1, 20) = 15.45, p = .0008, MSE = 397].

Process Measures. Our first process measure is total number of targets that were checked at least once per DMT. Clearly, if subjects were doing a thorough job this number would be 4 for DMT-4 and 6 for DMT-6. Although we do not have this information for the Table condition, we do have it for the two lockout conditions (see Figure 4) and it is not surprising to find a significant main effect of number of alternatives [F (1, 20) = 33.87, p = .0001, MSE = 18.34] with DMT-4 checking an average of 2.82 targets versus 3.74 for DMT-6. However, this absolute increase masks a relative decrease as DMT-4 checked 72% of their targets versus 62% for DMT-6.

More interesting for our purposes is the difference in number checked across the two lockout conditions. Although 0-Lock checked slightly more targets than 2-Lock (3.62 versus 2.94) this difference was not significant (p = .24). No other comparisons were significant.

Our second measure of process is the number of rechecks per DMT. If a threat value was checked once, how likely was it to be rechecked? As the proportion correct and number checked varied between DMT-4 and DMT-6, we were somewhat surprised that the number of rechecks was constant (F < 1). It is somewhat less surprising that more rechecks were done for 0-Lock than for 2-Lock [F (1, 20) = 44.63, p = .0001, MSE = 4.57]. However, it does surprise us that the 2-Lock condition made almost no rechecks (see Figure 5). None of the interactions were significant (F < 1).

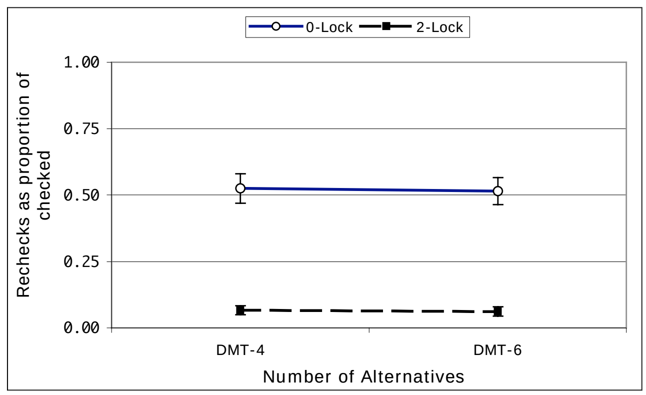

Figure 5: Rechecks as a proportion of those checked at least once. (Error bars show the standard error.)

Our third process measure is the time per check or recheck. We know from Figure 4 that 0-Lock performed more checks per DMT than 2-Lock. However, after subtracting 2-s for each check, the analysis of time per DMT showed that 0-Lock spent as much time per DMT as did 2-Lock. Hence, the time per check must be greater for 2-Lock than 0-Lock. We tested this conjecture in our final process analysis.

Time per check or recheck (after subtracting 2-s for each check made by 2-Lock) yielded a significant difference between lockout conditions [F (1, 20) = 7.98, p = 0.01, MSE = 374]. Even after subtracting 2-s per check, 2-Lock spent over twice as much time per check as 0-Lock (7.2-s versus 3.1-s). Interestingly enough, no other comparisons were significant—neither number of alternatives (DMT-4 versus DMT-6, F < 1) nor any interactions.

Discussion of Results

The Classification results suggest that the three between-subject conditions (Table, 0-Lock, and 2-Lock) were equivalent as measured by their performance during the four practice scenarios. Performance on classification increased across the eight scenarios in the decision making part of the study. This increase suggests that subjects were still taking the classification task very seriously.

The classification score differences between conditions during scenarios 5-12 appear to reflect the differences in time spent on the decision-making task. As the Table condition spent < 3-s per DMT compared to 16-s for 0-Lock and 24-s for 2-Lock they had more time to devote to the classification task. (Although there were significant differences between groups on the mean number of DMTs per scenario, these differences were small – Table = 3.4, 0-Lock = 2.9, and 2-Lock = 2.7 DMTs per scenario.)

All groups did well on the decision-making task though the Table group did the best. Table also spent much less time per decision than did the other two groups. The time to locate and move the mouse to the screen position of the target contributed to time spent per check by each of the Lock groups. However, although the search and movement costs were similar for 0-Lock and 2-Lock, the 0-Lock group made more rechecks than did the 2-Lock and this difference was constant across DMT-4 and DMT-6. Likewise, after subtracting time for the 2-s lockout, time per check was over twice as great for 2-Lock than for 0-Lock. What factors can explain these patterns?

Discussion

The current study addresses three limits to traditional research on the tradeoff of effectiveness for efficiency in decision-making. First, rather than counting the steps required for an expert agent to execute a decision-making algorithm, we counted the actual steps taken by human subjects during the process of decision-making and measured the duration of those steps. This approach provides better evidence for what people actually do when they make a decision and exposes important intermediary steps not captured by the traditional approach. For example, the current data reveals that the 0-Lock group performs many rechecks of threat value during decision-making. The necessity to check a step more than once implies that the requirement to hold the currently highest threat value in memory while searching for another target is an important sub-step that is affected by memory limits.

Second, by varying the interface design of the decision-making task, we have begun to disentangle the cost of a step in a decision-making algorithm from the cost due to how a step is implemented in a given task environment. It is obvious that the 0-Lock and 2-Lock conditions required more visual search and more motor movement than did the Table condition. In addition, the necessity to search for the next target while holding the currently highest threat value and its target identification number in memory adds a significant cognitive cost to the lockout conditions as compared to the Table.

Of great interest to us is that the additional 2-s per check imposed on the 2-Lock condition seems responsible for the vast differences in process and the slight differences in outcome between lockout conditions. 0-Lock rechecked more targets per decision-making trial while spending half as long on each check or recheck than did 2-Lock. Although there was nothing preventing subjects in the lockout conditions from rechecking the same number of targets or spending the same amount of time per check and recheck, they differed on both of these measures. Apparently differences in lockout costs led the two groups of subjects to adopt two different solutions to the problem of comparing a new threat value to the currently highest threat value. Encoding of location is a fairly automatic outcome of locating a target on a screen (Ehret, 2002). For 0-Lock, after a target had been found once, the cost of reacquiring that target was relatively low. This low reacquisition cost led 0-Lock to adopt a strategy of minimum memory encoding (as judged by the time spent per check) and more reliance on rechecks. For the 2-Lock group, the 2-s lockout did not simply add a delay in the time to access threat value, it also added 2-s to the retention interval for previously encoded threat values as well as for previously encoded target locations. As time for retrieving an item from memory varies with its activation level, we interpret the additional time per check of 2-Lock over 0-Lock as reflecting additional time spent retrieving old information from memory as well as a longer encoding time in anticipation of a longer retention interval.

Third, our experiment helps to move decision-making studies from static to more dynamic paradigms. Time spent on the decision-making task took time away from performing the classification task. Subjects had spent the first two hours of the study learning and practicing the classification task. During the last three hours we encouraged them to continue working hard on classification and to attempt to improve their performance. The data indicate that all groups improved their classification performance throughout the 8 decision-making scenarios.

The pressure to do well on the classification task apparently led subjects in the lockout conditions to satisfice on the decision-making task. As reported earlier, only 72% of the DMT-4 targets and 62% of the DMT-6 targets were checked on any given decision-making trial.

Summary & Conclusions

The study shows that small changes in the cost of interactive behavior may lead to changes in the strategy adopted for decision-making as well as to differences in how a step in the same strategy is implemented. The low cost of scanning the target-column for threat values led the Table condition to use all of the data to achieve near perfect performance in decision-making. In contrast, the lockout conditions satisficed by using less than 100% of the target data.

Although the two lockout conditions did not differ in the amount of information accessed, the differences in lockout time led each group of subjects to implement the information access step in very different ways. The 0-Lock group adopted an interaction-intensive procedure that made good use of perceptual–motor operations to minimize memory load. In contrast, the 2-Lock group adopted a memory-intensive procedure that maximized memory load and minimized lockout time per alternative. The different procedures adopted by the different groups reflect an adaptation of cognition, perception, and action to the cost structure or soft constraints (Gray & Fu, 2004) of the task environment.

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