Consideration of Strategy-Specific Adaptive Decision Support

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***Abstract*—The objective of adaptive decision support is to make the decision task easier and to improve the performance of a human's decision making. In this study, we investigate whether decision support systems should adapt to the strategies used by the decision maker, or if particular decision support designs are effective regardless of the strategy the user is inclined to use. We examine decision support system architecture and system match/mismatch with strategy as independent variables to determine the effects on accuracy, speed, and effort. Human-in-the-loop experimentation was used to determine the efficacy of two decision support architectures, one designed to support heuristic decision making and another to support analytic decision making. Both heuristic and analytic aids, led to faster decision making with no degradation in performance. Both aids also led to improved accuracy over the participants' baseline performance. In addition, the decision aids led to a drop in information access (a proxy for effort) with no degradation in performance. However, the experiment revealed no interaction effects between decision strategies and aid type. The results of this study should be considered in the design of decision support systems when determining if adding complexity to the system is truly beneficial. A more simplistic decision support tool may be sufficient to help decision makers make faster decisions with no negative impact on performance and to improve the decision making accuracy for users of all archetypes of decision strategies.**

***Index Terms*—decision making, decision support, heuristics, information acquisition**

I. Introduction

Humans are often asked to make decisions in complex domains where the decision space is too large to be fully explorable and the environment creates uncertainty. This creates a space where AI-tools can be invaluable, working to reduce and synthesize data. However, how best to use humans as experts in conjunction with AI decision support systems (DSS) is an open research question. The objective of adaptive decision support is to improve the performance of the human's decision making, as well as, to make the decision task easier. However, DSS, even the proactive and/or adaptive support paradigms, tend to increase rather than decrease complexity of the decision making process for the user.

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Currently, decision support tools do not consider the decision maker's tendencies and problem approach, and thus cannot adapt to different archetypes of decision makers. This puts the user in conflict with the method of support provided by the DSS. Decision strategies exist on a spectrum from heuristic to analytic strategies. A heuristic strategy ignores parts of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods [7]. An analytic strategy, on the other hand, seeks to weigh all the available information to identify an optimal solution. Analytic strategies are generally slower, more complex, and are highly dependent on working memory capacity [10]. Analytic and heuristic styles are treated as opposites on the continuum of decision making strategies; as one moves from analytic to heuristic processes, exact solutions are replaced by approximate, "good enough" solutions that may not be optimal [11]. Information processing in decision making can either be thought of as option-wise or attribute-wise. In option-wise processing, a single option is considered with all its attribute value before another option is processed. In attribute-wise processing, a single attribute is processed for all options before the next attribute in considered [14]. Heuristic strategies are thought to make attribute-wise evaluations, while analytic strategies make option-wise evaluations. Interestingly, both types of decision strategies have been shown to be accurate and effective. Decision support tools, often by default, assume that decision makers use analytic strategies, despite the abundance of literature suggesting humans are often reliant on heuristic decision making strategies [15]–[19]. Morrison et al. [21] point out that is critical to design decision aids which support the wide range of decision strategies if these aids are to be implemented in real-world, complex environments. Systems that do not properly support these types of heuristic decision strategies have been shown to negatively impact the workflow of the very users they aim to support [22]. Canellas and Feigh [13] devised effective rules for heuristic information acquisition in decision support. Follow on studies revealed that both heuristic and analytic information acquisition support can lead to faster, and in some cases more accurate decision making with less information [20], and differences in decision strategy adoption may explain significant differences in decision performance [23]. However, the environments for each of these studies was

a more simplistic, binary decision choice with four binary cues. It is unknown if these findings will hold in more complex testbeds.

In this study, we investigate the value of aids designed to support heuristic or analytic decision making. We transition into a more complex, realistic decision environment using a simulated geo-spatial emergency preparedness and response scenario which requires a series of 10 distinct decisions utilizing six decision attributes and a decision option space of 100 possible choices where decision support is altered to provide option-wise or attribute-wise aid [14]. This work examines the impact of this distinction, as well as tests and quantifies the potential benefits from inferring decision strategies and using the distinction to improve human-agent team performance. We seek to answer two primary research questions:

1) What form of decision support (option-wise or attribute-wise) improves performance (accuracy, effort, time to complete)?
2) Does decision support that aligns with natural decision strategy improve performance over strategy-aid mismatch?

II. Methodology

This section describes the experimental design, setup and apparatus, as well as, the methods used to identify the decision strategies used by participants.

A. Experimental Task

An artificial decision making environment was designed to simulate a disaster scenario in which the participants would act as disaster relief planners [4], [5]. In this role, the participant must decide where to place resources within a city prior to and throughout the progression of a natural disaster. The task was to select the best sites to place key resources (e.g. food, water, medicine) in anticipation of an oncoming storm. The storm was updated 10 times and the participant was given the opportunity to update the resource location at each storm update. The participants' goal was to maximize the utility of these resources to those affected by the disaster. The task environment was designed to simulate real-world decisions made sequentially with dynamic information change over ten time steps. The interface in Part 1 consisted of two main areas (shown in Fig. 1): the left hand side holds a list of six information attributes ('Data sources') the participants may choose to review, the right-hand side shows a map of the affected city. The participant could drag and drop the red pin shown on the map. The information attribute buttons allowed the participant to view a heatmap overlay of the relative utility of that information attribute on the city map. For example, the flooding attribute indicates where the flooding is most severe (dark red/black) and where it is not severe (green). Participants were provided with six information attributes: current storm (dynamic), flooding (dynamic), power outages (dynamic), socioeconomic status (static), population density (static), and no-go zones (static). At each decision step, the environment was updated, and the participant decided where to move their resource based on the new information. The participant was tasked with using the six attributes available to place the resource in the "best" location assuming each attribute was weighted equally. The participants were given the ability to click through the various attributes to display associated heat maps, and subsequently to select a single location to place the resource. Once the location was selected, the participant was required to click to submit the decision choice. After submission of a choice, the dynamic resources were updated. This sequence was repeated 10 times [3]. Participants were scored using an equal weighting strategy with cue values equal to the sum of the utility values with a min-max normalization applied. This created a scoring system in which the location with the highest criterion value received a score of 100, while the lowest criterion value location was scored as 0. The average utility in a grid space selected by the participant was taken as the representative utility for the entire grid space. Utility is a measure of how "good" a grid space is. The utility values were scored in 15 color swatches at each pixel, where green was the given a value of 1 and black was given a value of 0. More detail about the distribution of swatch values and utility scores can be found in [3]. Participants were briefed on how their performance would be measured.

B. Experiment Design

The study was designed as a two-part experiment. In Part 1 of the experiment, participants were asked to complete a decision task similar to that of the geo-spatial experiment described in previous studies [4]. They were asked to determine the best location to place a resource at each time step during a storm hazard scenario. Participants were then classified into decision process groups determined through a process tracing technique developed in previous work [3] and briefly summarized below. 90 participants were invited back through stratified random sampling.

In Part 2 of the study, participants were placed into one of three experimental conditions: heuristic aid, analytic aid, or control (no aid). Participants were told that in this part of the study that they would have access to an AI decision aid that was designed to make the task easier for them. The heuristic aid provided an attribute reduction to the participant by combining four of the attributes into a single composite attribute, as shown in Figure 2. This reduced the decision space from 600 to 300 grid spaces. The analytic aid provided option space reduction by eliminating 50% of the options, as shown in Figure 3. Spaces with utility values in the top 25% and bottom 25% of options were left so as not to artificially inflate scores. This aid also reduced the decision space from 600 to 300. The 'control' or 'no aid' condition provided a baseline of performance changes from Part 1 to Part 2 of the experiment, shown in Figure 1. This could account for any learning effects between trials. The decision space was not altered from the original 600. We compared the effects of aid type and strategy implemented on accuracy and effort in Part 2, as well as any interaction effects between aid type and strategy.

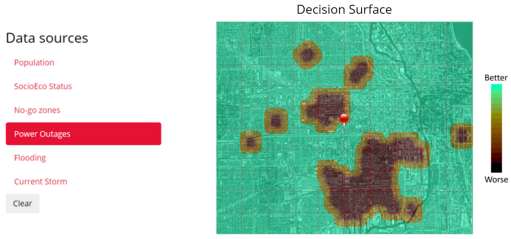


Fig. 1: Control Decision Aid. Participants completed Part 1 of the study using this interface. Those that we invited back for Part 2 and were assigned to the control group also used this interface for Part 2.

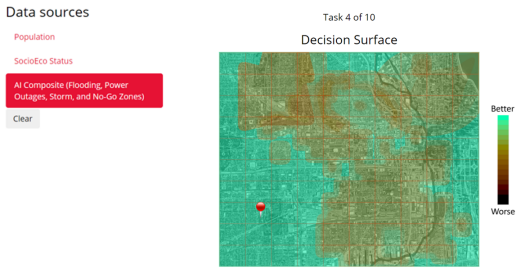


Fig. 2: Heuristic Decision Aid. The heuristic decision aid is design to aid in attribute-wise decision making by reducing the attribute space reduction from six to three.

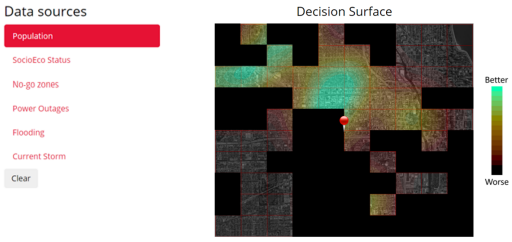


Fig. 3: Analytic Decision Aid. The analytic decision aid is design to aid in option-wise decision making by reducing the option space reduction from 100 to 50.

C. Participants

Data was collect for 178 participants in Part 1, and 90 participants in Part 2. Of the participants, 40% were male and 60% were female. Ages of participants ranged from 19-76 years old with a median age of 31. All participants spoke English, resided in the U.S., and reported no color blindness. Data was collected through the crowdsourcing platform, Prolific. The experiment was hosted on an experiment building platform, Gorilla. As an artifact of the poor data sometimes obtained in online crowdsourcing studies, the bottom 20% of participants were removed from consideration for Part 2 based on poor performance. Evaluation of performance was based on the average utility value of the grid location selected (described in the methodology section).

D. Strategy Identification

Participants were classified into decision process groups, $\leq$ 2 dominant attributes, 3 dominant attributes, or $\geq$ 4 dominant attributes, using a Partial Least Squares Regression (PLS-R) proposed and tested in previous work [3]. We provide a brief description of the method; further information can be found in [3].

We used the PLS-R to classify the grouping of decision strategy by uncovering the relationship between the behavioral data (mouse clicks, dwell time on each attribute) and outcome data (performance on each attribute). The PLS-R approach is uniquely suited to this problem structure. This problem is complex, with multicollinear independent variables, and an indirect measure for the dependent variables, as well as a larger number of variables for regression than measured observations. PLS-R technique can be used with data that contains correlated independent variables [24]. The technique constructs new independent variables, known as components, as linear combinations of the original independent variables. Similar to a Multiple Linear Regression (MLR), PLS-R seeks to find a combination of the independent variables that best fit the dependent variable(s). Additionally, like a Principal Components Analysis (PCA), PLS-R attempts to identify combinations of independent variables with large variance to identify those that are most significant. Unlike MLR and PCA, PLS-R combines information about the variance of both the independent and dependent variables, while considering correlations among them. For our problem, the PLS-R approach provides information about the relative importance of each resource to a participants decision choice, and which features from their behavioral data correlated most strongly with the used resources.

It is important first to clarify how the results of the PLS-R discussed below should be interpreted. We are not simply identifying what attributes were selected, which could simply be tallied. We instead examined how the interaction behavior with each attribute (the frequency and length of use over time) relates to performance over time (overall utility and individual attribute utility). Further, it should be noted that the PLS-R provided more granular information than was required for the strategy levels used to categorize the users. We instead use one level of abstraction. We assume here that only the number of attributes is sufficient to determine if the decision maker is heuristic or analytic, not which attributes they rely on. Thus we make no inference about whether participants are relying on good or bad heuristics, only that the strategy is heuristic in nature.

III. Results

In this section we explore the impact of both decision aid, provided by the researchers, and decision strategy, implemented by the participant, on performance and workload (mouse clicks and time-to-complete).

The results were analyzed using one-way and two-way ANOVAs to determine statistical significance. To answer the first research question, we used a two-way ANOVA. The two

factors tested were 'decision aid' and 'decision strategy'. Decision aid has three levels: heuristic, analytic, none (control). This represents the type of decision aid the participants were given in Part 2 of the experiment. Decision strategy has 3 levels: heuristic, analytic, or mixed. This factor represents the decision strategy used by the participant in Part 1 (classified by the Partial Least Squares Regression described below).

The second research question was analyzed using a one-way ANOVA. The independent variable is the strategy/aid alignment. This factor has 2 levels: match or mismatch. The dependent variables for both tests were accuracy (performance), and number of mouse clicks and time-to-complete (used as a proxy for workload). Unless otherwise noted, all assumptions for both analyses were met.

1) Strategy Groups: The distribution of decision strategies from Part 1 of the experiment, given in Figure 4, showed a similar distribution of strategies to those in previous experiments [3]. Participants using a 1 or 2-attribute strategy were grouped as heuristic strategy users. There were 11 participants in the 1-attribute strategy group and 54 participants in the 2-attribute grouping, totaling 65 participants classified as heuristic strategy users. The participants that were labeled as 4 and 5-attribute users were grouped as analytic strategy users. This strategy grouping contained 40 participants. The largest strategy group is the 3-attribute strategies group containing 74 of the 178 participants. These participants were characterized as using a mixed strategy approach. No participants were found to have successfully used all 6 attributes. One participant was labeled with an unknown strategy; unknown labels are given when the PLS-R cannot find any attribute that was consistently used in a way that was predictive of the user's performance. Using the results of the PLS-R, participants were invited back to complete Part 2 of the experiment.

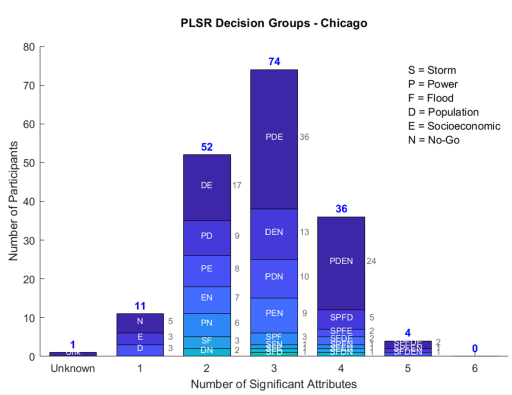


Fig. 4: Strategy classification for Part 1 using the PLS-R labeling method

A. Impact of Decision Aid on Performance

We begin by testing the changes in accuracy from Part 1 to Part 2 of the experiment. Part 1 results consider all participants that completed Part 1 of the study in a satisfactory manner (low-effort responses and bottom quartile removed). Part 2 results include all participants that were invited back to complete Part 2 of the study. Participants were invited back in three balance groups and were given either one of two types of decision aid or no decision aid, described previously. The change in performance between Parts 1 and 2 between groups that were given a decision aid and the group that was not provided an aid is given in Figure 5. The x-axis represents the time step (10 storm updates) and the y-axis represents the change in performance from Part 1 to Part 2 of the experiment. There was no improvement (p = 0.5) between Part 1 and Part 2 by participants that were not given an aid, depicted in yellow, i.e. there are no learning effects or improvement as a result of more experience. A one-way ANOVA showed that there was significant improvement (p = 0.0017, μ = 0.047) in decision making accuracy from participants that were given a decision aid in Part 2, depicted in black. Thus, there is a clear advantage to using a decision aid.

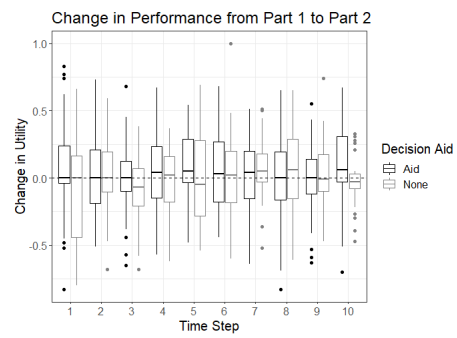
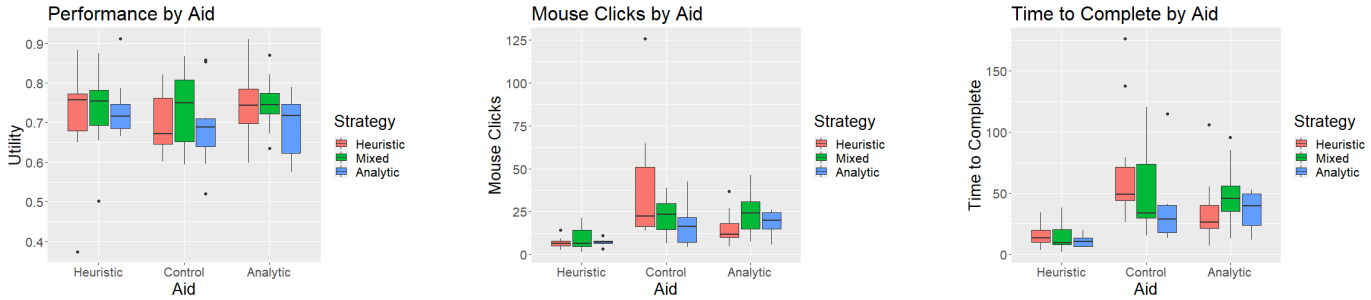


Fig. 5: Change in performance between Part 1 and Part 2 of the experiment. The groups given a decision aid are depicted in black and the group not provided an aid is given in gray. The group provided with a decision aid had significant improvements in performance while the control group showed no change in performance.

Next, we examine how decision strategy affects performance. A one-way ANOVA was used to show that 'mixed' strategy participants performed significantly better by over 8% (p=0.0485, μ = 0.086) between trials compared to the 'analytic' strategy when no aid was given, but not in the conditions where a decision aid was given, shown in Figure 6. Analytic strategy users under-performed in the baseline, but they performed as well as the other strategy groups when using an aid. This result indicates that the decision aid can boost performance of the lowest performers to bring them up to the performance standard of the other strategy groups. We then explored how a strategy-aid match or mismatch impacted performance i.e. participants using an aid aligned with their strategy, heuristic aid with a strategy labeled as heuristic. A two-way ANOVA showed that aid and strategy both significantly impacted performance (p = 0.03 and p = 0.009, μ = 0.0424 and μ = 0.068, for strategy and aid respectively) over the baseline. However, there were no interaction effects between strategy and aid and no difference between aid conditions. In summary, the results of this analysis revealed the decision



(a) (b) (c)

Fig. 6: The overall approach. (a) The performance of participants by aid and strategy groupings; (b) Number of mouse clicks; (c) Average time to complete a task

aids introduced here were equally effective regardless of users' decision strategy. There exist no significant differences in performance between the strategy grouping within each aid type, i.e. no interaction effects. However, decision aids can reduce the performance disparities between strategy groups.

B. Impact of Decision Aid on Workload

We used two effort metrics to estimate the effects of decision aid on workload, number of mouse clicks and the time it took to complete the study. Given that the previous section revealed minimal differences in performance among groups in Part 2, we do not need to control for performance in our workload estimates. There was a significant effect of decision aid on participants' time to complete a task while controlling for strategy. An ANOVA showed decision aid does impact ($p < 1.7e\text{-}6$) time to complete. A planned contrast revealed that having an analytic aid was associated with a significant decrease ($p < 5.05e\text{-}5$, $\mu = 11.47$) in time to complete, and being presented with the heuristic aid was associated with a further decrease ($p < 0.0002$, $\mu = 27.42$) in time regardless of the strategy of the participant.

It was also found that there was a significant effect of decision aid on participants' mouse clicks while controlling for strategy. An ANOVA showed decision aid does impact ($p < 3.99e\text{-}5$) number of mouse clicks. We then ran a second planned contrast which revealed that having an analytic decision aid was associated with a significant decrease ($p < 0.0003$, $\mu = 6.5$) in mouse clicks, and that being presented with the heuristic aid was associated with a further decrease ($p < 0.0032$, $\mu = 12.17$) in mouse clicks.

In summary, there were significant differences in workload for those presented with a decision aid versus those that were not provided an aid. Being presented with a decision aid led to a reduction in time-to-complete the study as well as fewer mouse clicks over all. In both cases, the heuristic aid (attribute-wise) led to a significant decrease in workload when compared to the analytic aid (option-wise).

IV. Discussion

It is critical to the design of DSS to support the types of decision strategies people use in real-world environments [21]. Traditionally, DSS bias towards an assumed analytic decision approach. We observe in this experiment a wide variety of information seeking and processing behaviors, with a slight preference towards the heuristic end of the spectrum over analytic. The majority of participants adopted the 'mixed' 3-attribute decision strategy. However, there are enough users at the analytic end of the spectrum that we must have the capacity to support these as well. Our goal in this experiment was to determine if a decision aid designed to support a particular type of decision strategy would be beneficial in complex decision environments. To make this determination we seek to answer two primary research questions.

To the first research question: both forms of decision aid led to more accurate decisions between trials when compared to the control group. However, differences in accuracy between the between the two types of aid were not statistically significant. These results indicate that both attribute-wise and option-wise aid have the potential to improve performance at the same levels in deployed DSS. As for the workload metrics, both aid types led to faster decisions with no degradation in performance. Our results showed that option-wise aid led to significantly faster decisions over the baseline while maintaining consistent performance levels, and the attribute-wise aid led to significantly faster decision compared to both the baseline and option-wise aid. Faster decisions without any losses in level of performance could have high impact in domains like military decision support where warfighters are often ask to make complex decisions like whether a target has malicious intent in a time-limited environment [23]. We show evidence that attribute-wise aid is best suited for faster decision making. Lastly, we found that both decision aids led to a reduction in information access, with the attribute-wise aid leading to a significant reduction over the option-wise aid and baseline condition. This is likely because the attribute-wise aid allowed for passive information acquisition leading to better retention of the available attributes. Heinke (2019) found that active information acquisition leads to decreased attention capacities spent on a piece of information [25]. The composite attribute allowed the users in the attribute-wise aid group to have more passive information access leading to an ability to retain more information from the attributes that were

viewed, thus reducing the need from active acquisition (fewer clicks).

To the second research question: no, we did not find sufficient evidence that a strategy-aid match was significant in altering performance in this decision making task. We instead found that one type of aid (the attribute-wise aid) led to improved performance regardless of the participants' natural strategy. This finding indicates that we can reduce cognitive load for all strategy types with a single type of aid. Relying on more passive information access with attribute-wise decision support reduces workload and decreases the time to make decisions for all decision makers and should be considered in DSS design. This may be related to limitations in working memory. We identified a tendency to overly dwell on visually complicated attributes while ignoring dynamic attributes. It may be that participants' working memory was poorly distributed and that attribute-wise support better targets supporting the working memory.

A. Limitations

The results support that attribute-wise support improved decision making for all strategy archetypes. This does not support the hypothesis that adaptive support is necessary but rather heuristic support is necessary. It is difficult to determine if this due to the nature of the support or if the distinction between similar strategies on the strategy continuum is not meaningful in this context. There does not exist a clear distinction between analytic, heuristic, and mixed strategies in the results. This indicates that this split may not have much value in this task domain, or alternatively, it may mean that using information seeking as our basis for classification is insufficient to capture actual information processing.

V. Conclusions

The goal of this work was to determine how different forms of decision support affect the performance and workload of various decision strategy archetypes. We present a two part experiment in which participants were asked to solve a serious of dynamic decision tasks. Participants were then classified in decision strategy archetypes and invited back to the second part of the study where they were exposed to a decision aid aimed at supporting heuristic or analytic decision making, or placed in the control group. We found that all types of decision strategy archetype benefited most from the heuristic (attribute-wise) support. Our findings indicate that reducing the need for active information access in favor for a combined attribute (passive information access) leads to faster and lower effort decision with no degradation or slight improvement in decision making accuracy. Our results provide evidence that attribute-wise support provides benefits to a wide range of decision makers and should be explored further. Future work should investigate a broader range of heuristic decision support and in tasks that have a spectrum of alignment towards heuristic and analytic strategies.

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