Intuitive or Deliberative? Decision Process Implications for Space Situational Awareness

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ABSTRACT

What is a good decision? How can good decisions be facilitated? Building SSA and taking the optimal course of action (COA) requires human operators to make reliable, accurate decisions. Achieving consistently high levels of decision making is a challenge because SSA tasking confronts considerable uncertainty, time pressure, and complex interactions. The decision science literature is ripe with debates about the benefits and pitfalls of intuition, responsible for snap decisions, and reasoning which is more deliberative [1]. This paper proposes a model for applying these insights to gain understanding and improve designs for the operational community. Among the most robust findings in the literature is the fact that the manner in which a choice is presented has tremendous power to influence the selection [2,3,4]. If managed properly with training and engineered systems, decision making can be optimized by mitigating the vulnerabilities and augmenting the capabilities of human decision makers. Thus, designers should embrace the responsibility and opportunity to facilitate better decisions in the field.

1. DECISION SCIENCE: INTUTION AND REASONING

What is a good decision? How can good decisions be facilitated? These are two ponderous questions that can elude satisfactory resolution in complex domains. Yet answers to these questions are vitally important to defending and promoting the space-based interests of the United States. Building Space Situational Awareness (SSA) and taking the optimal course of action (COA) continually requires human operators to make reliable, accurate decisions. Achieving consistently high levels of decision making is a challenge because SSA tasking confronts considerable uncertainty, time pressure, and complex interactions. Despite significant advances in computing power and artificial intelligence (AI), few critical decisions are made without a human decision maker in the loop. This is because human operators inject a needed diversity of expert knowledge, experience, adaptability, and the authority required to successfully execute SSA tasking.

Evaluating the quality of a decision can be elusive (as can bounding *a decision*); in order to constrain this discussion, "rational choice" will tend toward the economic conceptualizations such as maximizing utility and selection consistency. Expected value computations and maximizing utility have a long history as the *de facto* decision process [5]. Using that as a measure, one could determine "goodness" of choosing between the higher expected reward for a gamble that presents a 50% chance of winning $100 over a 90% chance of winning $25. Another litmus test for a good decision in the rational world is that choices (and thus decision makers) should be consistent. For example, if choice A is preferred to choice B, and B preferred to C, than A should be preferred over choice C as well. These early foundations fostered a process encouraging decision makers to list the pros and cons of a decision, perhaps use a weighting schema, but one way or another weigh the future benefit (or harm) of making a selection. The result, as sought by the rationalist models, should drive toward higher utility.

However, connate in human decision processes are mechanisms working against logical, rational thought. Even experts (in their domain), show vulnerabilities in decision making and the empirical research continually generates findings that transcend expertise, rank, and domain. A stronger understanding of the application of decision science could allow system developers to better design tools and craft decision contexts to facilitate better decisions. This paper will highlight several potential improvement opportunities of particular interest to SSA.

A wealth of literature on human decision making discussing rational and irrational outcomes exists, proposing varied prescriptive and descriptive models of judgment and decision making [1,6,7,8]. Though consensus among theorists remains elusive, a mounting body of literature shows that the rational, economic models are more brittle than originally believed, and deliberate listing and evaluation of all options is NOT representative of how many decision are made. Emerging is a substantial body of research has eschewed the rational models in response to the poor fit often encountered between the predictions of utility theories and experimental observations of human behavior. In particular, experts in operational settings seem to select the best COA with limited deliberative thought and consideration of the pros and cons of each possible choice [9,10]. A framework gaining interest lately describes two systems predominantly at work: *intuition* and *reasoning* [1,11]. *Intuition* is fast, automatic, and parallel contrasted with the more effortful, deliberative, and sequential *reasoning*.

However, adhering to a path of empirical findings does little to disambiguate what should be the standard of practice. For example, the merits, quality, and purpose of intuition are continually debated. One body of researchers calls intuition a hallmark of expertise responsible for rapid, optimal decisions in the face of adversity [9]. Others espouse intuition as vulnerability where biases lay decision traps leading to unfavorable choices [4]. Gaining favor in academic labs and popular science discussions, these dual process theories also offer promise for improving decision support systems. Though no one theory seems able to withstand all operational settings in all conditions, hybrid approaches hold promise for addressing the diversity of decision conditions encountered in the field. Many findings are showing sufficient value for information architects or system/interface designers to engineer effective decision support tools.

2. DUAL PROCESSES: ERROR AND SUCCESS

Instead of impugning theories, we hope to formulate a useful model for applying these insights to gain understanding and improve designs for the operational community. Our belief is that intuition and reasoning (i.e, deliberation) are both important elements in successful decision making. If managed properly with training and engineered systems, decision making can be optimized by mitigating the vulnerabilities and augmenting the capabilities inherent in human decision processes at the intuitive and deliberative levels. To document this approach, a full-factorial dual process theory is proposed (Fig. 1):

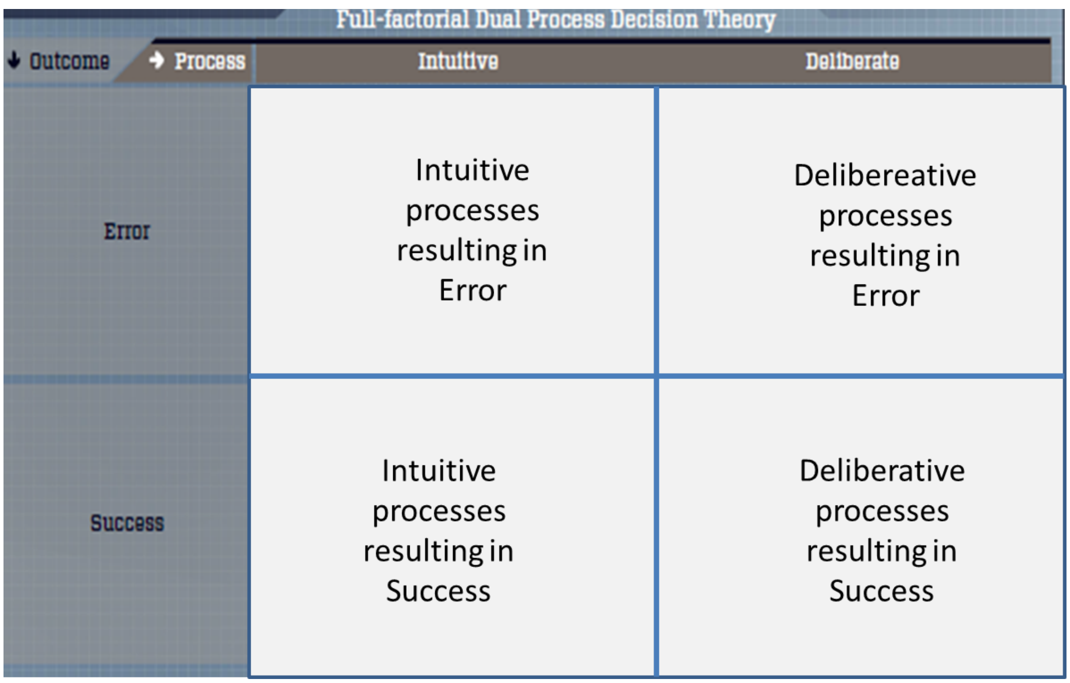

Fig. 1. Full factorial dual process decision theory.

Commitment to a hybrid model is consistent with a data driven-approach in which empirical results, not dogmatic adherence to a theory, guides selection and application of principles, mechanics, and manipulations for decision support services. Since there is evidence that the intuitive and deliberative systems can produce both successes and errors, these results should be studied and applied to better understand under what circumstances errors and successes are the most likely outcome. Below, we provide examples from the literature, and have recast the inquiries to approach SSA interests.

2.1 <u>Intuitive Error</u>

A telescope and its filter together cost $1100. The telescope costs $1000 more than the filter. How much does the filter cost?

This question is adapted from the well-known Bat and Ball problem [12] which elicits an erroneous answer by approximately 80% of the respondents (which included student populations from Harvard, MIT, and Princeton). In the original problem the bat and ball together cost $1.10 and asks participants to identify the price of the ball if the bat costs $1 more than the ball. The immediate response is usually 10 cents – which looks right, but is incorrect. If the bat was $1 more than a 10 cent ball, the total would be $1.10 + 0.10 = $1.20. Psychologists suggest the problem lends itself to such an efficient parsing that seems to satisfy the problem parameters, it is hard to inhibit this reactionary, incorrect response. Psychologists suggest if the reasoning system were used the error would be less likely (imagine writing out the full algebraic expression), and use this as an example of bias/heuristics introducing error.

2.2 <u>Intuitive Success</u>

Which person went on to greater power and success?

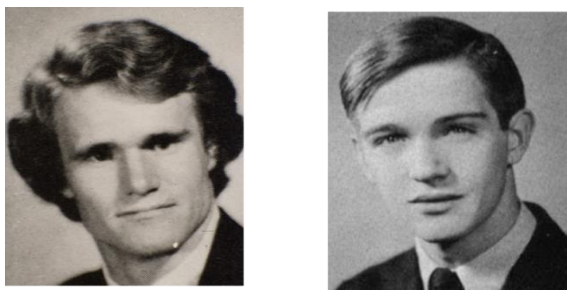

Fig. 2. Standardized yearbook photos for trait assessment.

These are not from the sample of photos used in the original study but most viewing these images (Fig. 2) will likely have an opinion (without much effort). In a documented triumph of the intuitive system, the researchers find participants make accurate assessments of another person's future success. Rule and Ambady [13] used high school yearbook photos of lawyers at prominent law firms, and asked participants to make rapid judgments and rate personal traits such as their power and likability. Those ratings were correlated with available performance data quantifying profitability of the lawyer shown in the photos. Their study revealed significant correlations with the participants' power ratings and the lawyers' profitability achievements suggesting participants were quite successful in making predictions of success from only a yearbook photo.

2.3 <u>Deliberative Error</u>

You are searching for a faint resident space object (RSO):
The probability that the object is in view of your sensor is 1%. If the object is present, there is an 80% chance your sensor will detect it. If the object is not present, the probability is 9.6% that your sensor will detect it anyway.
Last night your sensor recorded a hit.
What is the probability the RSO is present?

Gigerenzer & Hoffrage [14] posed this question (same values, different sensor and inquiry) to radiologists diagnosing breast cancer from a positive mammography. More than 90% of the expert population answered this question wrong! It's a complex calculation, and most are not experienced at making unassisted inference computations. A known obstacle is the propensity to ignore (or at least not fully value) base rate information, known as *base-rate neglect* [11]. Most physicians in the study guess the answer is between 70-90%. The correct answer is approximately 8% (more on this problem below).

2.4 Deliberative Success

Which city has a larger population?

(a) Philadelphia

(b) San Diego

Using German cities and participants, Gigerenzer and Goldstein [15] posed a similar question requiring participants to infer the relative size of city populations and give an answer. Despite not knowing the actual populations, people often succeeded in determining the correct answer. The researchers theorize participants were able to explore their own knowledge (unlike the probability question above) and search for relevant cues such as approximate or relative location, whether or not it is a capital, or perhaps something related to their major industries. For the problem above, without knowing for certain, one might build a case for Philadelphia in that it has a longer history as an American city, or is part of the dense east coast megalopolis. On the other hand, San Diego is part of the booming west, and anyone stuck in traffic there might overestimate the population. Following up on these results Goldstein & Gigerenzer [16] promoted a "recognition heuristic" in which a lack of recognition was also valuable information and found that students from Germany and Turkey (less familiar with American cities) could also perform well when provided additional cues (though also found a diminishing returns function with substantially more cues). The 2012 U.S. Census estimate (http://www.census.gov/) provides the following population figures:

Table 1. Population estimates for cities problem.

Philadelphia:	1,547,607
San Diego	1,338,348

3. DISCUSSION AND INTERVENTION

How can system designers take action to reduce errors and facilitate success? There are mixed findings as to whether simply making people aware of bias traps can help avoid these mistakes. Results exist from studies in which participants had the intellect and warning to avoid bias-induced mistakes, but still erred [17]. In contrast, a study in medical decision making [18] showed a reasonable improvement (across specialties) in which education/awareness improved scores on an Inventory of Cognitive Biases in Medicine (ICBM).

If the goal is to assist decision makers, questions of how, where, and when are reasonable to ask. To help address these elements of designing decision support systems, a Decision Intervention Spectrum (Fig. 3) is introduced. The axis is one of relative time and anchored on a decision point. Progressing along the spectrum in time brings one from a period well before a decision is made, to the time immediately around the decision, and also extending after the decision point. All of these instances may have a critical impact on the time of decision (or next decision).

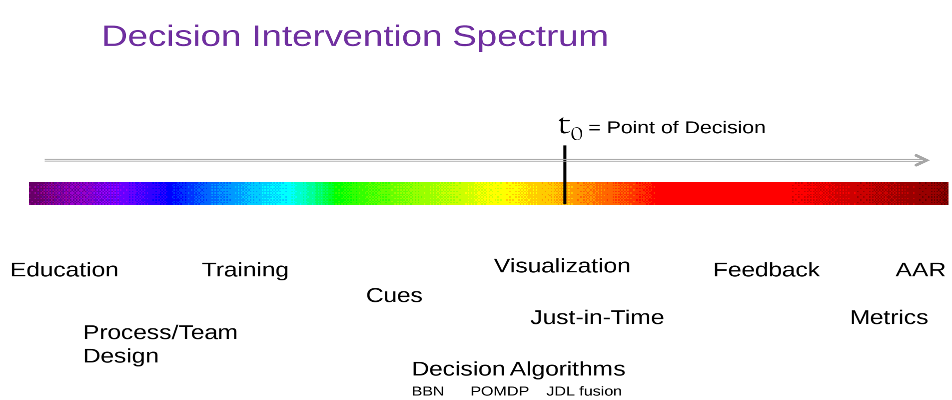

Fig. 3 The Decision Intervention Spectrum and a subset of methods available relative to the time of decision.

Once a decision on where/when to act is selected (training, real-time), the interventions must be constructed. Information presentation is more than choosing fonts and colors on the interface. Developers must acknowledge that the presentation of information can shape the success, frustration, and workload of operators. Good design can facilitate better understanding, more accurate predictions, and computations that are more accurate. For example, noting the difficulties humans have with Bayesian computations, Gigerenzer and Hoffrage [14] provided a presentation alternative to conditional probabilities. They termed this approach 'natural frequency' and the method uses countable cases instead of assigned values between 0 and 1. Using the mammogram inquiry (stated above) they hypothesized that a natural frequency approach would facilitate more accurate, less taxing computations and aid in arriving at the correct incidence of breast cancer given a positive mammogram. The distinction between the presentation styles is captured below (Fig. 4).

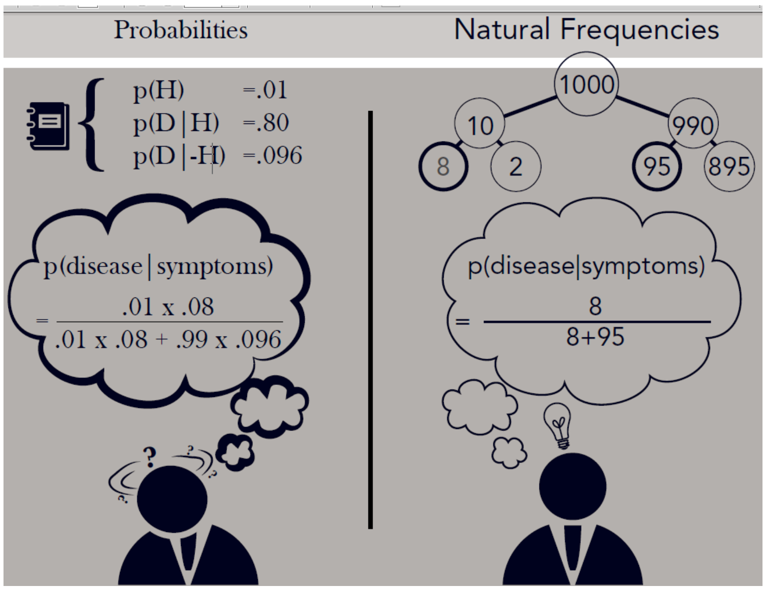

Fig. 4. Alternate presentaion of conditional probabilities and natural frequencies.

Start by imagining 1000 women. Given the base rate information (0.01), 10 women have the disease and 990 do not. Using natural frequencies enables one to more effortlessly compute and retain accurate numbers for the numerator and denominator by making it easy to count those with disease and without disease. Applying the hit and false alarm rate to the diseased (10) and non-diseased (990) facilitates the computation of how many positive results are likely to emerge (denominator). Using such manipulations, correct response rates climbed from approximately 20% to over 80% [14].

Among the most robust findings in the literature is the fact that the manner in which a choice is presented has tremendous power to influence the selection [2,3,4]. Mechanisms such as manipulating alternatives, changing defaults, adding decoys, and overwhelming with options have shown a staggering ability to prod consumers to make different buy decisions [2] or even convert previously non-participating people into willing organ donors [3]. Thus, designers should embrace the responsibility and opportunity to facilitate better decisions in the field.

4. REFERENCES

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