Overcoming Decision Making Bias: Training Implications for Intelligence and Leadership

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ABSTRACT

Recent military and homeland security events have made public officials, the media, and the public skeptical of the conclusions produced by intelligence analysts. Expert panels investigating the causes of intelligence failures sometimes list biases in judgment and decision making during analysis as a contributing factor. Experimental findings from cognitive and social psychology and decision science are typically cited to make this inference.

Decision making or analytic biases may indeed influence intelligence products, but findings from the bias literature may be over-generalized. Given that individuals can easily be biased, are flawed thinking and judgments inevitable? Conversely, can analysts be trained to understand and detect their biases, and use that knowledge in applying heuristics capable of counteracting biases, to minimize mistakes in judgment?

This paper addresses training approaches that can influence the mental processes that decision makers follow during the intelligence-producing task. After a brief literature review of decision making bias, analytic methods are described and training interventions outlined that might mitigate biases in real-world analytic situations. Finally, the training approaches that have influenced development of leadership training are described where, again, awareness of potential biased reasoning is necessary for decision makers engaged in critical warfighting tasks.

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INTRODUCTION

Intelligence analysts are decision makers who judge and reason from collected material to properly analyze it. In light of recent military and homeland security events, some doubts and suspicions have been cast upon intelligence analysts and their reports. Although investigations into the cause of failure often point to systemic problems, many also claim that intelligence failures resulted from analysts' decision making biases (cf. Heuer, 2004). Recent reviews have cited experimental findings from cognitive and social psychology as partial explanations for decision making biases (e.g., Heuer, 1999).

While it is true that the cognitive psychology literature is replete with findings showing how decision making biases influence conclusions, the authors contend that rote application of the bias literature does not satisfactorily explain intelligence failures. For instance, the context in which decision making takes place (physical work environment, amount and quality of rich data, prior knowledge of the domain, ability to communicate and exchange hypotheses and interpretations, task completion time, degree of pressure to produce) certainly plays a role separate from the de-contextualized situations that psychologists often study. Similarly, a view of analysts as rational thinkers can be challenged by largely overlooked literature involving naturalistic decision making.

From a training perspective, the question becomes whether or not biased products are inevitable or, conversely, whether or not analysts can be taught to understand and accept their biases, and use that knowledge in applying heuristics capable of counteracting biases, to minimize mistakes in judgment. This paper describes training approaches that influence the process that decision makers follow for an intelligence task, to help decision makers confront biases.

Finally, in this paper these same training approaches are shown to be able to influence leadership training where, again, leaders who reason and make decisions need an awareness of how biases can adversely affect their decisions during critical warfighting tasks.

BIAS IN INTELLIGENCE ANALYSTS' DECISION MAKING

To limit this paper's length, two key terms are defined. First, *decision making* is used to describe the cognitive processes that intelligence analysts follow in producing analyses; this is in contrast with the common usage of decision making in intelligence as the decisive actions that consumers of intelligence analyses take. Also, decision making is extended to include judgment and reasoning (Pitz & Sachs, 1984) but not problem solving or decision aids. There are certainly commonalities in the cognitive constructs underlying or relating decision making and problem solving, such as representation, persuasion, cognitive resource limitations, and expertise, however the two are often treated as separate research areas (Simon et al., 1986). Decision aids (i.e., decision support systems), meanwhile, are those tools that are used in applied settings to aid decision makers, hence rely on cognitive results from decision making research. To the extent possible idiosyncratic or individual difference variables are avoided that could affect decision making, such as personality profiles, cognitive style, cognitive load, and reaction to stress (Johnston, 2005).

Second, *bias* is extended to include reasoning or judgmental error to include those processes that deal with uncertainty, source of information, inferential basis, conflict, integration, and tradeoff (Pitz & Sachs, 1984). Situations of particular interest are those relevant to intelligence analysts where bias might be exhibited, such as those requiring constraints of uncertainty, knowledge, time, or accountability. What constitutes bias or error is also considered; assumptions about the goals individuals may be trying to achieve are considered whenever possible, since what constitutes 'good' judgment or 'successful' decision making or reasoning may be context-specific.

Types of Bias

Many specific forms of bias and error appear in the literature. A number derive from the heuristics individuals use to make decisions and reason under constraints of uncertainty, incomplete knowledge, time, or accountability. A sample of biases relevant to the representativeness and availability heuristics, for instance, includes:

- The *law of small numbers*, where individuals are not fully sensitive to the size of a sample on which an event is based (Kahneman & Tversky, 1972).
- *Ignoring base rates* and *stereotyping*, where individuals fail to consider relative frequencies of two choices and/or base decisions on preconceived notions of characteristics of given choices (Johnson & Finke, 1985; Kahneman & Tversky, 1973).
- *Accessibility bias*, where any factor besides frequency that causes a choice or event to become more readily available (e.g., familiarity, salience, vividness) may lead to biased responses to that choice or event (Tversky & Kahneman, 1973).
- *Framing bias*, such that the phraseology used to describe alternative outcomes (e.g., positive vs. negative) influences the decision (Tversky & Kahneman, 1981).
- *Anchoring bias*, in which decision makers are influenced by given or initial values and respond or judge based on those values (Tversky & Kahneman, 1974).

Individuals exhibit other biases that seem to be less related to heuristic use than related to use of decision making strategies or associations (Arkes, 1991). Some examples are:

- *Information order bias*, by which decision makers derive different conclusions depending on the order in which they receive information. Individuals tend to view new information in terms of an already established mental model (Augustine & Coovert, 1991), even to the point of disregarding the new information entirely if it does not fit their preconceived notions (Janis & Mann, 1977).
- *Sunk cost effects* that lead decision makers to take into account effort already expended in addressing a problem, whether or not those costs are relevant to the current decision making context (Arkes & Ayton, 1999).
- *Pre-decisional distortion*, the pre-choice biasing of attributes of choices depending on those most favored by decision makers (Carlson & Pearo, 2004). For instance, individuals rate evidence higher when it matches their own beliefs than when it does not match their beliefs (Redding & Reppucci, 1999). Similarly, decision makers might ‘mirror image’ (Taylor, 2005), that is, interpret behavior of others by reflecting on mores inherent in their country, religion, or culture.
- The associated *desirability*, *confirmation*, *selection*, and *belief biases* that describe the tendencies to over-predict desirable outcomes and under-predict unwanted outcomes (Olsen, 1997), seek and weight evidence more strongly that conforms to previous expectations (Klayman & Ha, 1987), and accept conclusions that are believable rather than logically valid (Evans, 1989) or that appear not to conflict with decision makers’ values (Jervis, 1976). Individuals generally believe strongly in their initial judgments and maintain these beliefs despite contradictory information (Tversky & Kahneman, 1974).
- *Process biases*, where decision makers fail to generate alternative outcomes, estimate the impact of counter-examples or counter-factual information, examine costs vs. benefits of alternative outcomes, reconsider originally rejected alternatives, and determine how to monitor results (e.g., Herek, Janis, & Huth, 1987; Tversky & Kahneman, 1986).
- *Outcome biases* (Baron & Hershey, 1988; Subbotin, 1996) that imply that knowledge of the outcome of a decision influences the rating of decisions. An unfavorable outcome of a good decision (i.e., one that individuals believe would be most likely to lead to success on the next occasion) leads individuals to switch away from that decision due to negative emotional responses to the outcome (Ratner & Herbst, 2005). Individuals may control the expression of their judgments, though, depending on their comfort of feeling of entitlement to do so (Corneille et al., 1999).

Naturalistic Decision Making

Arguments for unavoidable bias appear to conflate bias with knowledge-based processing. The literatures on expert problem solving and scientific discovery (see Klahr & Simon, 1999) suggest that bias is not inevitable. Instead, knowledge-directed encoding, search, hypothesis formation, selection, and testing, and systematic critical reasoning lead to accurate (unbiased) discoveries of new information and correction of errors, based on theoretical and intuitive predictions.

Still, the explanations from classical studies demonstrating that individuals show biases in decision making were influential, as they were couched in terms of a rational thinker, a legacy of the information processing paradigm then prevalent in areas outside of cognitive psychology such as economic theory and modeling. Studies seemed to show that individuals’ judgments deviate from what logic (e.g., Bayes’ rule, utility theory) would dictate: We make mistakes in attributing cause to events; misestimate relationships among variables; fail to revise beliefs in response to new evidence; confuse sample proportion with sample dispersion; and use different prediction models from one time to another despite no changes in data provided (Johnston, 2005; Lassiter et al., 2002; Wegener & Petty, 1995; Winman, Hansson, & Juslin, 2004). The conclusions seemed to be that decision makers are *ir*rational under constraints (Klein, 1989); given their limited mental resources, individuals' judgments often do not reflect algorithmic or logical flow, but instead rely on use of heuristics that can lead to seemingly biased (irrational) decisions.

Furthermore, the classical studies, in general, presented tasks that differ considerably from those that intelligence analysts, in particular, receive. In those studies, seldom if ever was persuasive argumentation and justification of choices required, with negative consequences attached to errors. In those studies, perceptual biases were shown that involved minimal content, duration, or cognitive effort, and the tasks rarely involved exposure to large amounts of conceptual information that was to be understood and synthesized. These characteristics are all different from intelligence analyses. Kahneman & Frederick (2005) distinguish between relatively rapid decisions that are made intuitively, and relatively effortful decisions that are made via a supervisory process that reasons about intuitive decisions. The nature of an intelligence analyst's information-processing environment conforms more closely to the latter whereas the empirical foundation for the early strong claims of biased decision making was the former.

Somewhat supportive explanations portray individuals as *fast and frugal* decision makers (Gigerenzer et al., 1999) rather than irrational, and perfectly able to make complex decisions and judgments given an appropriate, naturalistic context. Classes of simple strategies that decision makers follow include initial-reason decision making for choice, elimination models for categorization, limited-capacity detection of relationships, and satisficing heuristics for sequential search (Kareev, 1995, 2000; Mellers, Schwartz, & Cooke, 1998). These simple strategies can perform comparably to more complex algorithms (Snook, Taylor, & Bennell, 2004). For instance, individuals appear to be poor at Bayesian reasoning, but when they are given problems that present the relevant information in absolute rather than relative frequencies, or as percentage probabilities of a set of events rather than single events, or even just as appropriate 'tokens' that individuals are wired to be able to individuate rather than perceive as whole objects, then performance turns out to be in line with Bayesian theory (Brase, Cosmides, & Tooby, 1998; Koehler, 1996; though see Newell, Weston, & Shanks, 2003), that is, completely rational.

In contrast to positing decision makers as irrational (or just biased), the heuristics that decision makers follow, particularly under constraint, may be viewed as adaptive, in that they reduce and focus what is being attended to and processed. Under constraint, basic reactions dominate, and decision makers tend to reduce the search for and acceptance of new information and simplify the evaluation of choices presented. Labels given to this updated view of 'biased' decision making are *recognition primed decision making* or more generally *naturalistic decision making* (Klein, 1989; Lipshitz et al., 2001), and are characterized by immediate recognition of many situations or events (as is accomplished via expertise; Chi, Glaser, & Farr, 1988), satisficing rather than seeking the best solution, and evaluating what option first comes to mind rather than comparing options. Thus, instead of rational versus irrational, decision making should be considered ecologically valid or not depending on how well matched parameters of the decision are to those natural to individuals (Brase et al., 1998; see also Kahneman & Frederick, 2004, regarding natural assessments).

TRAINING IMPLICATIONS

Intelligence Analyst Training Implications

Intelligence analysts are decision makers who judge and reason from collected material to properly analyze it (Clark, 2004; Tatarka, 2002). (In the intelligence world those who determine courses of action, that is the *consumers* of intelligence products, are often labeled decision makers, but the term is used here to also describe those who interpret what the data mean, that is the *producers* of intelligence products.) The question then arises: What biases in decision making and judgment, especially those associated with use of heuristics, would occur under conditions natural to intelligence analysts? The answers are important if intelligence analysts might be trained to employ the best strategies in a given context to confront decision making biases.

Current Approaches

To seek answers, a first step is to study currently trained analytic methods – some 200 methods that intelligence analysts might choose (see Bringsjord et al., 2006; Clauser & Weir, 1976; Fishbein & Treverton, 2005; George, 2004; Heuer, 2004; Johnston, 2005; Marrin, 2004; Pherson, 2005; Rieber & Thomason, 2005). Presented here is a partial categorization of methods, including reasons why the methods might help counteract decision making biases.

Certain methods force analysts to generate alternative interpretations of the material, to anticipate the unanticipated. Indeed, the authors of the 9/11 Commission report recommended "institutionalizing imagination" as a means of forcing analysts out of a comfortable box. For instance, *alternative scenarios forecasting* has analysts develop multiple plausible alternatives as each new piece of information is added, or as interactions among pieces of information are identified. *What if* analysis, similarly, has analysts systematically vary key assumptions and speculate how these variations might influence analytic interpretations. *Backward tracing* is presuming that a given scenario has occurred, and trying to explain what drove the scenario to occur. *Quadrant crunching*, a derivative technique for generating a set of alternatives when faced with little data or uncertainty, helps analysts identify gaps or unknowns and set priorities for analyses of subsequent material. *Alternative futures analysis* has analysts try to identify key 'driving forces' that, if altered or differently weighted, would shape plausible alternative future scenarios. *Brainstorming* allows any and all ideas or concepts to be proposed for how to interpret data. When tied with scenario-based simulation, these methods enable analysts to trace different paths through a decision or outcome tree based on variations in analytic interpretations. As a result, these methods help analysts confront outcome biases such as representativeness, availability, accessibility, and stereotyping.

Other methods force analysts to question the material or assumptions about the material. They require that analysts maintain awareness of their own strengths, weaknesses, and tendencies. A *key assumptions check*, for instance, requires that analysts explicitly specify key analytic assumptions, forcing them to question or criticize each assumption and to determine gaps or sensitivities associated with the data. During *linchpin analysis*, analysts present evidence to support their premises and consider what evidence might make those premises untenable. To keep analysts aware of the need to verify data validity, *deception detection checklists* make analysts determine whether or not, or to what degree of confidence, differences in the data (e.g., as would be the case if the data were meant to be deceptive) would dramatically change analytic conclusions. These types of methods help analysts confront biases such as confirmation, stereotyping, framing, selection, belief, and pre-decisional distortion.

Still other methods force analysts to defend or reinterpret findings. A *red cell analysis* involves taking the perspective of the opposition to predict its behavior. In *devil's advocacy* analysts or colleagues challenge findings by building alternative explanations. *Analysis of competing hypotheses* takes analysts through a structured process, forcing them to look for inconsistencies while disproving hypotheses rather than deriving conclusions. *A-team / B-team analysis* forces competition between analysts in producing or defending competing hypotheses. The commonality among these methods lies in their imposition of constant revisiting of data to manage process biases such as confirmation, anchoring, information order, pre-decisional distortion, and sunk costs.

Ongoing Work

Despite the availability of so many analytic methods, a dominant mode of analysis remains unstructured (intuition-based) assessment that may be prone to biases (Marrin, in preparation). The intelligence community is amidst a process of professionalization that will help formalize training (e.g., competencies, credentials, test scenarios) and work practices (e.g., job aids, check lists, methods of communication) to help analysts avoid or mitigate decision making biases, but community-wide practices are not yet formalized.

To further seek answers regarding natural decision making bias situations, the authors are conducting an experiment to characterize the cognitive processes and knowledge used by producers of high quality intelligence summaries and contrast their cognitive activities and behaviors with those used by less capable counterparts given the same intelligence development task. The experiment is using an information processing analysis to identify the cognitive processes and knowledge that yield exemplary performance, following procedures from studies of human problem solving, expert performance, and scientific discovery. (Results are to be reported by the time of the I/ITSEC 2007 conference.)

Automated and direct observation of participants' execution of an intelligence reporting assignment is providing material for analysis. Also, the intelligence product itself (a report) for each participant is being compared against 'gold-standard' intelligence products that expert staff provide, to assess organization, layout, word-to-image ratio, level of content, and referencing. Analyses are summarizing participants' means of gathering information to include extent of and specific wording of searches, electronic collaboration and with whom communications are done, abstracting of retrieved data, and variety of sources sought. The efforts involved in gathering information and formatting the final product include the time spent, the level-of-effort suggested by keystroke analyses, the number of tools (e.g., document formatting, image editing, Internet searching programs) used, and the goodness of the final product as a function of these measures.

These cognitive task analyses of actual performance, beyond assessment of methodologies, will inform findings of specific and detailed intelligence-producing mental activities. By considering the types of mental activities, their sequence and their usage, most-appropriate training for analysts will follow (for related work, see Staszewski, 2006). Thus, as elaborated next, when the analyses find participants engaged in, for example, confirmatory searches or limited hypothesis testing, tailored remediation will provide instruction on overcoming confirmation biases and generation of competing hypotheses.

Training Analyst Cognitive Processes

Though analytic decision makers may not be irrational, they cannot generally and systematically use all available information. Consequently, contextual and subjective factors will lead the analyst to use heuristics like availability and representativeness. Further, analysts like all decision makers approach a problem with a mindset (Betts, 1980; Heuer, 1999; O'Connor, 2005) that influences basic assumptions and activates expected patterns. But training can enable these analysts to counteract some of the biases associated with these heuristics – or at least confront biases with methodological tools – and appear more rational in their decisions.

For instance, it is possible to improve decision making by showing individuals how their decisions are influenced by factors like outcome biases and sunk costs, and by motivating them to confront these biases (Wilson & Brekke, 1994). Emphasizing the salience of additional costs to decisions, rather than sunk costs, moderates sunk cost effects (Tan & Yates, 1995), while pointing out tendencies toward certain outcomes raises decision makers' awareness and, at least under conditions that do not limit cognitive effort, motivates them to seek additional information.

Training on critical thinking eliminates reasoning errors (Halpern, 1998), and training on comparative and analogical processes improves decision making (Idson et al., 2004), though generating the right scenarios and developing the right analogies is important (Bolton, 2003). The goals, meanwhile, that individuals set for themselves (or have set for them) influence decision making. The goal of accuracy, for example, tends to minimize outcome bias because it demands elaboration of information, whereas the goal of being able to defend one's decision enhances outcome biases by promoting selective processing of preferred outcomes (Agrawal & Maheswaran, 2005). Analysts thus need to be made aware of goal-directed effects on their decisions.

Similarly, the robustness of framing biases is attenuated by training (Fagley & Miller, 1987; Perrin et al., 2001). Training specifically in the content domain, or more broadly in decision theory, can lead to a deeper understanding of the problem that is less affected by the surface presentation (see Chi et al., 1988), so long as individuals know when to apply a learned normative (i.e., non-biased) rule and when to generalize it for similar problems (Wilson & Brekke, 1994). Another approach to overcoming framing biases is to learn to restate or reframe the problem (e.g., Hodgkinson et al., 1999, 2002), thereby requiring decision makers to question the understanding of the problem by gathering additional information. Exploring the context surrounding the problem (e.g., Dhar, Nowlis, & Sherman, 2000; Wegener & Petty, 1995) prompts decision makers to perceive different perspectives of the situation.

Additionally, an effective strategy for removing several kinds of biases from judgments, such as pre-decisional and outcome biases, is to train individuals to generate and consider plausible alternative outcomes for a decision (Hirt & Markman, 1995) or, when appropriate, to stimulate counterfactual thinking (Galinsky & Moskowitz, 2000). There is some evidence that learning to generate alternatives generalizes to making judgments in different domains (Hirt, Kardes, & Markman, 2004).

As described, current methods already force analysts to gather additional information, check key assumptions, take different perspectives, and generate alternative outcomes. Hence the training need is to have analysts understand the strategic uses of these methods.

Further, analysts are often given incentive or are under time and production pressures to derive results that fit with existing understanding (i.e., conventional wisdom), and confirmation biases contribute to sometimes unsound decision making (Davis, 2004). Motivating analysts to expend effort to confront these biases involves having them keep in mind when policy stakes and organizational prestige are high, how complex issues may be, how uncertain information may be, and when hypothesis testing and argumentation are necessary.

A training focus can be on information and its sources. Analysts tend to assign greater importance to information coming from confidential sources than open sources, they tend to assign value to information coming from other analysts whose work they respect or whose work in the past has proven relevant, and their prior beliefs influence the evaluation of incoming data. In forming impressions of the accuracy of information, having the motivation to form accurate impressions helps, even when the source of information has negative connotation (Neuberg, 1989). In addition, the extent to which decision makers are held accountable for the accuracy of decisions influences the range of information used to make judgments, though non-diagnostic information may adversely influence how discriminating analysts' judgments are of the information (Tetlock & Boettger, 1989; Salvemini, Reilly, & Smither, 1993).

Another training focus can be on the big picture, on how information becomes intelligence that fits with what is known, particularly through collaboration. For instance, *sense-making* is a collective, iterative process of sharing individual intuitive judgments to develop narratives to make sense of found patterns and data anomalies (Fishbein & Treverton, 2005). Communication between analysts and content or field experts, even asynchronous communication, offers a way for analysts to quickly integrate a larger world view with their information, though the experts must be aware of analysts' level of knowledge of the topic (Bromme, Rambow, & Nuckles, 2001).

Some conditions impose particular trouble for analysts to counteract biases; these should be made known to the analysts. For instance, feedback on results of decisions is necessary to identify and address biases. Where results are delayed or not directly attributable to decisions, or where feedback is somehow degraded, decision makers cannot apply lessons learned (Marrin, 2005; Tversky & Kahneman, 1986). Similarly, when analysts cannot generate or access alternative results, or have low motivation to do so (Keinan, 1987), then they have no means of comparing alternative outcomes to assess any influence of biases. Finally, decision making under constraint, without decision support, leads to less elaborative processing of alternatives, less critical examination of 'distracting' information, less availability of 'bandwidth' to communicate with others, less toleration of ambiguity in data, and generally more risky decisions (Kowalski-Trakofler, Vaught, & Scharf, 2003).

Leadership Training Implications

Some of the training implications of overcoming decision making bias for intelligence analysts are applicable to leader training. One current application is for Signal officers. The intent is to support modularization of the U.S. Army into Brigade Combat Teams (BCT), which is pushing much of the decision making surrounding BCT networks to a Signal staff group whose responsibilities include planning, establishing, maintaining, and securing multiple communication networks. More specifically, the Signal staff must plan the network, detect anomalies in the implementation of the plan, identify and mitigate communications shortfalls, and report on network status. The training revolves around the Military Decision Making Process.

A key characteristic of leadership decision making is adaptability. An adaptive leader exhibits, among other traits, decisiveness yet comfort with uncertainty, and balance between reliance on technology vs. reliance on subordinate teams built through trust (IBCT, 2000). To train decisiveness requires deliberate practice within a wide variety of scenarios, so that appropriate responses become routine (Mueller-Hanson et al., 2005). However, to ensure comfort with uncertainty requires continual stress on revisiting assumptions and forecasting or retracing alternative outcomes. Similarly, to instill a reliance on technology requires extensive use of the technology so that the leader understands its strengths, but also its weaknesses, where person-to-person communications take over. Methods such as A-team / B-team analysis and deceptiveness checks enable the leader to begin to learn when and how to rely on information collected from disparate sources.

Much of the knowledge that a Signal officer brings to the task is tacit, able to be elicited but difficult to express (see Frank et al., in preparation). Training to acquire and practice tacit knowledge requires reflection on how actions, consequences, and conditions interplay. Methods such as backward tracing and analysis of competing hypotheses encourage such reflection, to confront availability and confirmatory biases, both during leadership activity (reflection-in-action) and before and after (reflection-on-action). Similarly, eliciting and being able to express the tacit knowledge that a leader has, so that new leaders may be trained on that knowledge, involves knowledge capture techniques similar to what if analysis and red cell analysis, where different perspectives are imposed on the leader and questioning of assumptions forces the leader to articulate or explain strategies and procedures.

PRACTICAL IMPLICATIONS

What these training implications don't address is the practice of analysts (or leaders) detecting self-bias. Without awareness of their biased processes, even using methods that confront some of their biased decision making, analysts can unwittingly produce biased products. Training to enable analysts to target self-awareness is no small feat, as it requires analysts to be able to explicitly understand what strategies they follow in choosing particular methods to develop and assess their products. A useful approach is to convince analysts to purposefully attempt different methods of analysis on occasion, to force them to state assumptions and defend or criticize results, to others or even just to themselves.

Furthermore, intelligence production is context-dependent, having a cycle that includes intelligence consumers (Clark, 2004). Policymakers use intelligence products to support their political, military, economic, social, informational, or infrastructural goals. Managers use analytic products to defend financial, technological, or human performance measures. These consumers might not be so blatant as to direct analysts to produce logically or computationally simple products, or direct analysts to assess material broadly rather than deeply or vice versa, but they might employ analytic products to serve preconceived ideas (O'Connor, 2005).

It may appear somewhat outside the scope of this paper, but sometimes analysts may need to refute the misuse of their products or to expose key assumptions that drove their analyses. In these cases, analysts must engage in meta-analysis, in that they must apply what they know about decision making biases at the analytic level to analogous biased reasoning at the organizational level. Hence, when they notice their products being employed to confirm ideas only, or to justify continuing along a path due to sunk costs, or when no critical thought is given to alternative scenarios or competing hypotheses, or when their or other analysts' products can be seen to involve only stereotyped or carefully framed components, then the same methods apply. Training on meta-analytic bias necessarily follows training on analytic bias, and though this type of meta-awareness is not yet well understood (Otani & Widner, 2005), it can be just as important.

CONCLUSION

There are predictable reasoning or judgmental errors that derive from intelligence analysts' information processing. Furthermore, any analytic product stems from the context in which it is produced, including the properties of information available (e.g., its completeness or deceptiveness), time and production pressures placed on the analyst, and the mindset of the analyst. A number of training approaches, though, help analysts to overcome these biases or mitigate their effects.

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