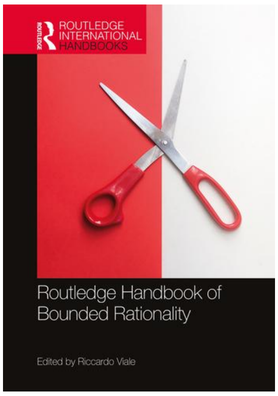

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COGNITIVE BIASES AND DEBIASING IN INTELLIGENCE ANALYSIS

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Introduction

Simon (1947, p. 79) boldly asserted that "It is impossible for the behavior of a single, isolated individual to reach any high degree of rationality." He recognized that rationality is bounded by limitations of the unaided human mind and by the complexity and uncertainty of the task environment (Simon, 1957). Simon (1956, 1990) believed that organisms are adapted to the structure of their environments. "Human rational behavior … is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990, p. 7). He believed that under such conditions people may opt to satisfice, i.e., settle on a "good enough" solution (Simon, 1956). Indeed, research has now identified a wide range of systematic deviations from normatively rational behavior, often referred to collectively as "cognitive biases" (for reviews, see Gilovich, Griffin, & Kahneman, 2002; Kahneman, 2011; Kahneman, Slovic, & Tversky, 1982).

However, as Katsikopoulos and Lan (2011) note, Simon also explored ways in which performance could be improved so that satisficing and boundedly rational behavior did not lead to poor outcomes. Similarly, in response to the findings regarding cognitive biases, researchers have begun to identify and test possible debiasing strategies (for reviews, see Arkes, 1991; Fischhoff, 1982; Larrick, 2004; Lilienfeld, Ammirati, & Landfield, 2009). Several classifications of cognitive bias have been proposed, and debiasing strategies may be informed by theories of how and why a bias may occur.

Fischhoff (1982) distinguishes between faulty decision makers, faulty tasks, and decision maker–task mismatches. Arkes (1991) focuses on the type of error made, distinguishing association-based errors (i.e., side-effects of the fact that triggering one concept in memory activates other, related concepts) from psychophysical errors based on risk aversion and our biased response to losses and gains, and strategy-based errors resulting from a person using a poor analytic strategy. Stanovich, Toplak, and West (2008) base their approach to bias on dual-process theories of cognition which distinguish System 1 thinking (i.e., fast, unconscious, automatic, associative, parallel processing, effortless, and intuitive) from System 2 thinking (i.e., slow, conscious, controlled, rule-based, sequential processing, effortful, and deliberative). Cognitive bias is considered to be the product of System 1, which can be mitigated when an individual uses System 2 to override a System 1 response. A successful override may fail to occur if, for example, there is a lack of effort/self-control ("override failures/cognitive miserliness"), a lack of knowledge of the correct strategy to use ("mindware gaps"), or use of a flawed strategy ("contaminated mindware"; see also Stanovich & West, 2000). Similarly, Kahneman, Slovic, and Tversky (1982) distinguish between comprehension errors (i.e., mindware gaps) and application errors (i.e., override failures or cognitive miserliness).

Dual-process theories of mind have been criticized and alternative accounts exist. Viale (2018; 2019) argues that the dual-process account is undermined by recent psychological and neuroscientific evidence which suggests that the cognitive processes involved in creative incubation and mind wandering are both unconscious and analytical. Alternatively, Hammond's (1996, 2000) cognitive continuum theory proposes that there are many "quasi-rational" modes of cognition that lie in between the poles of intuitive and analytic thinking, and which comprise different combinations of intuition and analysis (see also Sloman's 1996 view that intuition and analysis are interactive). According to Hammond, the mode of cognition applied to a task is determined by task properties and/or the experience the individual has with the task. Success on a task inhibits movement along the cognitive continuum (or change in cognitive mode) while failure stimulates it.

When working in an organizational context, Simon (1947, p. 79) believed that organizations can place "members in a psychological environment that will … provide them with the information needed to make decisions correctly." For instance, organizations can establish standard working practices, train individuals, and structure the work environment so that it encourages rational thinking and consistency or regularization of practice. In this chapter, we critically evaluate the solutions that intelligence analysis organizations have offered to combat cognitive bias in their intelligence analysts. We identify cognitive biases that may affect the practice of intelligence analysis and review debiasing strategies developed and tested by psychological research.

Intelligence analysis

The intelligence analyst must produce a coherent report that precisely communicates his/her conclusions about a current or future situation to a variety of consumers who may then make strategic and tactical decisions that affect national and international security. For example, what forces does North Korea have along the border with South Korea? What will be Russia's offensive cyber capability in 2025? Where are the headquarters of terror group X?

At its core, intelligence analysis is a cognitive task. Analysts must plan, search for, select, process, and interpret data in order to gain situational awareness and/or forecast an outcome of interest to customers. This is articulated in the generic analytic workflow (Dhami & Careless, 2015) which applies to different sorts of intelligence analysis (e.g., HUMINT, SIGNIT, as well as single and multi-source), conducted individually or in teams, for different purposes (e.g., strategic, tactical). The workflow is separated into six meaningfully different stages of activity that follow from one another, namely, capture requirements, plan analytic response, obtain data, process data, interpret outputs, and communicate conclusions.

The task of analysis is made difficult partly because the human mind is limited in terms of attention, perception, memory, and processing capacity, and partly because the task itself can be extremely constraining and demanding. Indeed, there may be not enough relevant data or there may be large volumes of data, the credibility of data sources may vary, the data may be formatted in different ways (e.g., structured/unstructured, textual/visual/audio), it may be ambiguous, unreliable, and sometimes intentionally misleading, and there may be time pressure and high stakes involved. This is further compounded by the lack of feedback which limits learning on how to perform analytic tasks.

It is no surprise, therefore, that critics have accused analysts of resorting to using simple heuristics which can lead to cognitive bias and error (Heuer, 1999). Some would even suggest that the only way to decide rationally is to use heuristics because no rules following normative canons of economic rationality may be applied (e.g., Gigerenzer, Todd, & the ABC Research Group, 1999). Nonetheless, heuristics can lead to systematic cognitive bias, and cognitive bias has been implicated in well-known intelligence failures such as the failure to find weapons of mass destruction in Iraq (Jervis, 2006). Although intelligence analysts are experts in their domain, this is unlikely to protect them from cognitive bias. Indeed, studies demonstrate that intelligence analysts are as susceptible to cognitive bias as anyone else (e.g., Cook & Smallman, 2008), and may be even more susceptible than non-experts (Reyna, Chick, Corbin, & Hsia, 2014). As we discuss in the next section, cognitive biases can manifest at each stage of the analytic workflow.

Cognitive biases in intelligence analysis

After a review of the extant literature on intelligence analysis and on cognitive biases, we identified at least 21 key biases that could affect individual analysis (rather than analysis conducted in groups/collaboratively). The biases can be assigned to stages of the analytic workflow based on an assessment of the cognitive tasks involved at each stage and how those might induce bias. Placing the biases along the workflow allows analysts, managers, and trainers to identify where issues may arise and can aid in tailoring debiasing support efforts.

For present purposes, we focus on eight biases that are particularly meaningful to one or more stages of the analytic workflow. These are described briefly below:

1 *Belief bias* (Evans, Barston, & Pollard, 1983) is the tendency to evaluate the logical strength of an argument based on the plausibility of its conclusion.
2 *Confirmation bias* can manifest in a variety of ways (see Klayman, 1995), i.e., remaining overconfident in an initial position, searching for evidence in a way that supports a favored viewpoint, interpreting evidence in a way that favors a preferred viewpoint, and resisting change or insufficiently adjusting confidence in a viewpoint in response to new conflicting evidence or when existing evidence is discredited.
3 *Explanation bias* (Ross, Lepper, Strack, & Steinmetz, 1977) refers to the idea that if you think about/imagine how or why an event may happen, you will then consider it more likely to happen than if you had not thought about it.
4 *Fluency effects* (Schwartz et al., 1991) refer to the idea that information which can be retrieved and/or processed fluently (e.g., because it is familiar) tends to be preferred and judged more likely and credible than less easily processed information (Reber & Schwarz, 1999; Tversky & Kahneman, 1973; Zajonc, 1968). When evaluating sources, this can lead to a preference for evidence received from an expert even if that expertise is irrelevant (also called expertise bias); overestimating the association between independent characteristics of a favored person or object (halo effect; Nisbett & Wilson, 1977); and evaluating people who share your characteristics more favorably than others who do not (similarity bias; Rand & Wexley, 1975). Some have suggested that fluency may sometimes be the most appropriate way to make decisions, at least where no other knowledge is available (Hertwig, Herzog, Schooler, & Reimer, 2008).
5 *The framing effect* has many facets (Tversky & Kahneman, 1981; see also Levin, Schneider, & Gaeth, 1998), i.e., the tendency for risk-aversion when a choice is framed as a gain (relative to the status quo), but risk-seeking when a choice is framed as a loss; making an evaluation

based on whether something is described as positive or negative; and choosing to engage in a behavior based on whether participation is described as advantageous or disadvantageous.

6 *Order effects* (see Hogarth & Einhorn, 1992) refer to the fact that the order in which information is presented affects the relative importance attached to it. Information presented first and last is particularly biasing.
7 *The planning fallacy* (Kahneman & Tversky, 1979) is the tendency to underestimate the time (and cost) required to complete a task by overlooking potential difficulties.
8 *Overconfidence* (Fischhoff, Slovic, & Lichtenstein, 1977) refers to when an individual's subjective confidence in the accuracy of his/her judgments is greater than the objective accuracy of those judgments.

These biases may manifest at various stages of the analytic workflow. At the *capture requirements* stage, analysts must understand the context for the intelligence question, including the customer's goal and how it will be achieved, and analysts should challenge this if necessary. Analytic performance at this stage can be affected by confirmation bias and framing. For instance, analysts might set out to look for evidence that confirms a customer's pre-existing assumptions or hypotheses rather than challenging these. In addition, the way an intelligence request is framed may bias the analysts' understanding of it (e.g., looking to determine how many casualties are likely to occur as a result of civil unrest rather than considering how many lives could be saved by one course of action or another).

In the *plan analytic response* stage, analysts must identify alternative methods that could be employed to answer the question, evaluate their potential effectiveness and efficiency, and prioritize how to proceed. Analytic performance may be affected by fluency effects and the planning fallacy. For instance, analysts may favor specific analytic lines to follow, consider particular information to be necessary to test hypotheses, and select methods for obtaining data that have been used recently or frequently in the past and therefore come to mind most easily. Analysts may also underestimate the time involved in completing the analytic task.

At the *obtain data* stage, analysts must select relevant data from the most appropriate sources in an efficient manner, as well as establish new sources of data if necessary. Performance at this stage may be affected by fluency effects, confirmation bias, and order effects. For instance, analysts' choice of data sources and search terms may be limited to those that come to mind most easily, partly because they have been used regularly or recently. In addition, analysts may be biased toward obtaining data from trusted experts (even if their expertise is inappropriate for the context in question), favored or familiar sources as well as sources that are similar to them (i.e., other intelligence organizations), believing them to be more credible. Analysts may search for new evidence in a way that favors their existing hypothesis (e.g., by avoiding sources likely to contradict the hypothesis). Data obtained first and last (e.g., in a list of search results) may be more likely to be filtered/selected even though these are not more reliable or valid.

At the *process data* stage, analysts must understand the 'raw' data, and this may involve collating, reformatting, and manipulating it using relevant tradecraft, tools, and technology. Here, analysts may suffer from fluency effects and confirmation bias. For instance, analysts may over-use analytic techniques that they are familiar with or use regularly. Data processing tasks such as identifying unexpected or anomalous results and generating visualizations may be biased toward favored analytic lines/hypotheses.

At the *interpret outputs* stage, analysts must evaluate alternative explanations for the (often incomplete) facts, and construct logical arguments to support conclusions as well as dismiss alternative ones, determine the degree of uncertainty in these conclusions, and identify any ambiguities. Here, analysts may be affected by belief bias, confirmation bias, and explanation bias. For instance, analysts may over-weight arguments that produce plausible conclusions rather than properly assess their logical strength. Analysts may be overconfident in an initial belief and so, even if they take an unbiased approach to new information, they will remain overconfident in their initial position. Analysts may reach conclusions about a hypothesis based on the presence of supporting rather than conflicting evidence. Analysts may interpret new evidence in a way that favors their existing hypothesis (e.g., by regarding supporting evidence as reliable and conflicting evidence as unreliable, or by interpreting ambiguous information in a way that supports a favored hypothesis). Analysts may be resistant to change so they insufficiently adjust their confidence in a hypothesis in response to new conflicting evidence or when existing evidence is discredited. By considering possible explanations for the data, analysts may conclude that those explanations are more likely than is really the case.

Finally, at the *communicate conclusions* stage, analysts must present the outcome of analysis in a clear and meaningful way; distinguishing fact from inference, highlighting the alternatives that were considered, and expressing uncertainty and confidence. Analytic performance at this stage may be affected by belief bias and overconfidence. For instance, where analysts have reached a plausible conclusion, they may overstate the strength of their supporting arguments or evidence. Analysts may not allow sufficiently for uncertainties and ambiguities in their reports.

Debiasing strategies

Intelligence organizations have made an attempt to help analysts overcome cognitive bias by investing in training analysts to use so-called structured analytic techniques (SATs) and in the development of specialized computer technologies to support and aid analysis. The intelligence community has largely eschewed psychologically informed and empirically tested cognitive debiasing interventions (Dhami, Mandel, Mellers, & Tetlock, 2015). Next, after a brief review of the intelligence community's preferred debiasing methods, we consider psychologically informed debiasing strategies relevant to the eight biases described above.

SATs (see Dhami, Belton, & Careless, 2016; Heuer & Pherson, 2014) are a collection of techniques designed to reduce cognitive bias. The primary rationale behind SATs is that externalizing and decomposing the cognitive process will result in bias mitigation. Some SATs, such as the Analysis of Competing Hypotheses (ACH), were developed specifically for use by intelligence analysts, while other SATs (e.g., the Delphi method) were originally used in other contexts but have since been applied in the intelligence analysis domain. However, to date, very few studies have tested whether SATs actually reduce bias. The research that does exist suggests that they may actually lead to errors such as base-rate neglect (e.g., Dhami, Belton, & Mandel, 2019; Mandel, Karvetski, & Dhami, 2018).

As Dhami et al. (2016) point out, SATs cannot guarantee accuracy. This is partly because they rely on the judgment skills of the analyst and his/her subjective input of the information and interpretation of the outputs. In addition, SATs may overcorrect one bias, potentially triggering an opposing bias, and the decomposition process can make judgments less reliable rather than more so (Chang, Berdini, Mandel, & Tetlock, 2017). Despite the limitations of SATs and the lack of evidence attesting to their efficacy, SATs often form part of the core skill set taught in analytic training programs (e.g., Marrin, 2008) and analysts are expected to apply them (e.g., UK MoD, 2013; US Government, 2009).

As mentioned, the intelligence community has also adopted different types of computer-based tools to support analysis (see Dhami, 2017). Indeed, there are currently a vast array of analytic tools available, and these can be used at different stages of the analytic workflow as they serve a variety of purposes. For instance, at the processing data stage, tools can be used to visualize data (e.g., Stasko, Gorg, Liu, & Singhal, 2007), perform network analysis and geospatial analysis, support argumentation (e.g., Kang & Stasko, 2011), and decision making (e.g., Svenson et al., 2010). In addition, some SATs, such as ACH, have been automated. Finally, "serious games" are video games that use technology and techniques from the entertainment sector to teach individuals to recognize and reduce cognitive biases. However, as with SATs, the ability of computer-based tools to reduce cognitive bias has generally not been empirically tested. A notable exception is serious games, which have been found to successfully reduce several biases, namely, confirmation bias, the fundamental attribution error, the bias blind spot, anchoring, the representativeness heuristic, and projection bias (e.g., Dunbar, Miller, et al., 2014; Morewedge et al., 2015; Mullinix et al., 2013; Shaw et al., 2016). These games involve interactive learning about biases and activities aimed at reducing them. The development of serious games has been informed by psychology.

The practical utility of computer-based tools may be limited because, as Dhami (2017) found in a recent survey of intelligence analysts, the lack of usability can be an important barrier to analysts' uptake of analytic tools. When there was a tradeoff between the usability and usefulness of a tool, analysts preferred usable tools over useful ones. In addition, like SATs, many computer-based tools rely on potentially biased subjective human inputs and interpretations of output (Büyükkurt & Büyükkurt, 1991; Montibeller & von Winterfeldt, 2015), which limits their ability to help analysts avoid bias and error. Despite this, the intelligence community considers analytic technology as potentially helpful, as illustrated by projects funded by the US Intelligence Advanced Research Projects Activity: (www.iarpa.gov/index.php/research-programs).

Psychologically informed interventions

Psychologists have investigated many different interventions for reducing cognitive bias. These are usually based on theories about the sources of bias, and empirically tested to examine their effectiveness in countering the bias. Table 37.1 provides a summary of the empirically tested debiasing strategies for the eight cognitive biases identified described earlier.

Psychologically informed and empirically tested debiasing interventions typically involve two elements. First, participants are given training or instructions that aim to increase understanding and awareness of cognitive biases. The goal here is to improve an individual's ability to identify tasks or situations where an intuitive response is likely to be biased, so that they can override their intuition with an appropriate deliberative strategy. Second, interventions aim to fill mindware gaps by teaching relevant rules (e.g., probability or logic), or specific strategies to use in a given task (e.g., consider the opposite of your original answer or unpack a task into component parts).

An alternative approach to debiasing involves restructuring the task environment to reduce biased behavior, either by encouraging more deliberative thinking or by inducing unbiased intuition. This kind of so-called "choice architecture" that "nudges" individuals towards better decisions (Thaler & Sunstein, 2008) has proved itself to be effective for promoting pro-social behaviors such as paying tax or becoming an organ donor and has become an increasingly popular policy-making tool (e.g., Hallsworth, Egan, Rutter & McCrae, 2018). In the public policy context, questions remain about whether some nudges may be unacceptably coercive (e.g., Viale, 2018, 2019). However, it is likely that there are many contexts within the intelligence community where choice architecture could usefully be employed to reduce biased thinking.

Table 37.1 Psychologically informed and empirically tested debiasing interventions

Cognitive bias	*Psychological intervention*
Belief bias	Evans, Newstead, Allen, and Pollard (1994) found that brief "instructional training in logical principles" reduced belief bias in basic logical reasoning tasks.
Confirmation bias	Several variations of the "consider-the-opposite" strategy have been found to reduce confirmation bias. For example, instructing individuals to imagine their response if given evidence pointed in the opposite direction reduced the tendency to discount conflicting evidence, and presenting conflicting evidence in advance of a search for information reduced the bias of that search towards supporting evidence (Lord, Lepper, & Preston, 1984). Similarly, instructions to consider multiple alternative hypotheses reduced subsequent belief perseverance (Lewandowsky et al., 2012). If too many alternatives are generated, this may undermine the mitigating effect of "consider-the-opposite" interventions because the difficulty of generating alternatives can undermine their perceived plausibility (Sanna, Schwartz, & Stocker, 2002). Fortunately, this "backfire" effect can be reduced by raising awareness of the difficulty of generating alternatives (Sanna & Schwartz, 2003). Actively searching for disconfirming evidence to falsify an initial hypothesis may also reduce confirmation bias (Lam, 2007).
Explanation bias	Considering multiple alternatives has been shown to reduce the explanation bias, as long as not too many alternatives are generated (Hirt & Markman, 1995; Sanna et al., 2002).
Fluency effects	"Consider-the-opposite" strategies of the kind successfully tested on confirmation bias and order effects may be effective here, since they aim to induce consideration of alternatives beyond those that spring to mind immediately. A simple, practical solution for biases relating to source evaluation is to get a second opinion from a colleague who is not familiar with the source and/or aggregate evidence from multiple sources wherever possible.
Framing effect	A range of strategies have been found to reduce the framing effect. These include: considering the opposite (Cheng, Wu & Lin, 2014); reframing the problem in an opposite way (Korobkin & Guthrie, 1998); listing advantages and disadvantages of two options before choosing between them (Almashat, Ayotte, Edelstein, & Margrett, 2008); giving reasons for the chosen option (Leboeuf & Shafir, 2003); presenting information in a frame-neutral way, for example, through graphical representations (Garcia-Retamero & Dhami, 2013); "causal cognitive mapping" or a node-link diagram of the variables used to make a decision and their cause-effect relationships (Hodgkinson, Bown, Maule, Glaister, & Pearman, 1999); scenario planning (Meissner & Wulf, 2013); and a strong warning message about the risk of the framing effect (Cheng & Wu, 2010)
Order effects	Mumma and Wilson (1995) found that considering the opposite of the first information item given and also sorting information based on diagnosticity removed the primacy effect, as did simply writing a list of the information items after viewing them on-screen. Ashton and Kennedy (2002) found that requiring individuals to rank information items by importance and then review them before making a judgment successfully removed the recency effect. Wickens, Ketels, Healy, Buck-Gengler, & Bourne (2010) found that instructing participants that newer data is likely to be more reliable increased the recency effect (when appropriate) but did not reduce the primacy effect. Logan and Fischman (2011) found that performing a simple manual task (i.e., rearranging a pair of water glasses) between viewing and recalling a list of words removed the recency effect, but not the primacy effect.

Table 37.1 Cont.

Cognitive bias	*Psychological intervention*
Overconfidence	Koriat, Lichtenstein, and Fischhoff (1980) found that overconfidence could be reduced using a form of the "consider-the-opposite" strategy, which involved listing counter-arguments to a preferred hypothesis or prediction. Multi-step strategies for eliciting forecasts in the form of confidence intervals have been found to reduce overconfidence (e.g., Speirs-Bridge et al., 2010). Simply instructing people on the risk of overconfidence when making judgments has also been found to have a debiasing effect (McGraw, Mellers, & Ritov, 2004).
Planning fallacy	Breaking down or "unpacking" the task into component parts and estimating the time needed for each can be an effective debiasing strategy, especially when the unpacking task is made relatively difficult, e.g., breaking the task into five rather than two steps (Kruger & Evans, 2004) and if individuals focus on obstacles to task completion (Peetz, Buehler, & Wilson, 2010). Thinking of multiple scenarios in which the task in question or similar tasks could take much more or less time has been found to reduce the planning fallacy in subsequent task time estimates (Newby-Clark, Ross, Buehler, Koehler, & Griffin, 2000). Taking an "outside view" of the task may also reduce the planning fallacy (Kahneman & Lovallo, 1993). Estimating the time another person would take to complete a task, based on that person's own estimate, improves estimation accuracy (Buehler, Griffin, & Ross, 1994). Estimates are somewhat more accurate when based on memories of the time taken to complete comparable tasks in the past (Buehler et al., 1994) and are likely to be even more accurate when benchmarked against the actual time taken to complete comparable tasks previously (Roy, Christenfeld, & McKenzie, 2005). Visualizing a third party completing the task can also mitigate bias (Buehler, Griffin, Lam, & Deslauriers, 2012). Backward planning, which involves working step-by-step back from the desired end goal, can also reduce the planning fallacy (Wiese, Buehler, & Griffin, 2016).

Conclusion

Intelligence analysts have been criticized for suffering from cognitive biases (Heuer, 1999), although there have been few empirical demonstrations of this. In this chapter, we identified eight biases applicable to the analytic workflow and we reviewed psychologically informed debiasing strategies that aim to counter those biases. The intelligence community's efforts to help their analysts become more rational thinkers may be inadequate because organizations rely on ad hoc SATs and a proliferation of computer-based tools that largely lack empirical evidence attesting to their efficacy. In addition, there seems to be little acknowledgment of the fact that SATs and computer-based tools may simply replace existing biases with new ones. In this sense, one could argue that intelligence organizations have failed to fulfill their function, as identified by Simon (1947), to provide analysts with an environment that encourages rational thinking.

The intelligence community has, to date, largely eschewed psychologically informed and empirically tested interventions. In essence, many of these interventions require the individual to stop and think before pursuing a course of action. As Simon (1947, p. 89) suggested, "If rationality is to be achieved, a period of hesitation must precede choice." Although further research is needed to confirm how well the effects of such interventions can be transferred to the intelligence analysis domain, this should not preclude their use in the meantime. Below, we conclude with a consideration of the potential challenges associated with debiasing people and the limitations of debiasing strategies, before highlighting the main barrier to debiasing in the intelligence analysis domain.

There are many challenges involved in successfully implementing any debiasing strategy. The first is the bias blind spot which is a meta-cognitive bias that refers to the tendency to believe that we are free of cognitive bias even though we recognize bias exists in others (Pronin, Lin, & Ross, 2002; West, Meserve, & Stanovich, 2012). This can make analysts resistant to training or instruction designed to mitigate cognitive biases since they will tend to think it does not apply to them. Second, individuals need to be convinced that debiasing is relevant to their work, and in order to reduce threats to self-esteem, they may need to be reassured that debiasing is about further enhancing their thinking rather than correcting cognitive faults. Indeed, it is often observed that analysts can be resistant to using debiasing techniques such as SATs or computer support tools (e.g., Trent, Voshell, & Patterson, 2007; Treverton & Gabbard, 2008). Third, the durability of the effects of most debiasing strategies is currently unknown (for exceptions, see the recent work on serious games which used follow-up periods between 8 and 12 weeks, e.g., Dunbar, Miller, et al., 2014; Morewedge et al., 2015; Mullinix et al., 2013; Shaw et al., 2016). Fourth, it is likely that individual differences such as personality, cognitive ability/style, and culture may affect how well people respond to debiasing strategies (Oreg & Bayazit, 2009; Stanovich & West, 2000), particularly as research suggests that individuals differ widely in their susceptibility to cognitive bias (e.g., Peters, 2012; Toplak, West, & Stanovich, 2011). Finally, some debiasing interventions may backfire, increasing rather than reducing the target bias (e.g., Sanna et al., 2002) or may even stimulate some other bias.

In addition, features of the intelligence analysis domain may make it difficult for intelligence organizations to build and maintain a psychological environment that is conducive to rational thinking. In particular, the intelligence community has traditionally held to the belief that intelligence analysis is a "tradecraft"—a skill that must be learnt "on-the-job" over a long period and which generates implicit knowledge handed down from one analyst to another. This hinders efforts to improve analysis through top-down approaches.

Despite the many challenges and barriers, there is scope for optimism. Simon (1947) observed that effective organizations enable individuals to think rationally. We suggest that by adopting an appropriately skeptical attitude to untested approaches such as SATs and some computer technologies, and by embracing a psychologically informed and empirically tested approach to reducing cognitive bias, intelligence organizations can assist their analysts to improve analytic performance.

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