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Intelligence Analysts' Strategies for Solving Analytic Tasks

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Abstract

Analytic performance may be assessed by the nature of the process applied to intelligence tasks and analysts are expected to use a 'critical' or deliberative mindset. However, there is little research on how analysts do their work. We report the findings of a quantitative survey of 113 intelligence analysts who were asked to report how often they would apply strategies involving more or less critical thinking when performing representative tasks along the analytic workflow. Analysts reported using ‘deliberative’ strategies significantly more often than ‘intuitive’ ones when capturing customer requirements, processing data, and communicating conclusions. Years of experience working in the intelligence community, skill level, analytic thinking training, and time spent working collaboratively (opposed to individually) were largely unrelated to reported strategy use. We discuss the implications of these findings for both improving intelligence analysis and developing an evidence-based approach to policy and practice in this domain.

Keywords: Intelligence analysis, analytic workflow, intuition, deliberation, critical thinking

Introduction

It is believed that the quality and accuracy of intelligence analysis will benefit from the use of critical thinking skills (see Harris & Spiker, 2011; Moore, 2007). According to cognitive scientists, critical thinking requires the use of System 2 or deliberative cognition (e.g., Evans & Over, 1996; Kahneman, 2003; Sloman, 1996). This is characterized as a conscious, controlled process that is shaped by formal education and intelligence. Deliberative thinking relies on working memory, and is a cognitively demanding, slow process which uses rule-based thinking and sequential processing of information. This is contrasted with System 1 or intuitive cognition, which is characterized as an unconscious, automatic process that is influenced by prior experience. Intuitive thinking does not rely on working memory. It requires little cognitive effort and is a fast process that uses associative thinking, and parallel processing of information. Researchers have empirically distinguished between the two modes of cognition and provided evidence of their operation (e.g., Hamm, 1988; Marewski & Melhorn, 2011; Rusou, Zakay, & Usher, 2013).

There are, however, contrasting views on the relative value of intuitive and deliberative thinking. For instance, whereas some believe that intuition is an indicator of expertise (e.g., Klein, 1989; see also Klein, 2008; Patterson & Eggleston, 2017), others view it as a default mode of cognition that operates when the more superior deliberative mode is unavailable (e.g., Tversky & Kahneman, 1974; see also Kahneman, 2011; Kahneman & Klein, 2009), while some consider the value of each mode to be determined by how well it matches the requirements of the task at hand (Hammond, 1996; 2000; 2010; see also Dhami & Thomson, 2012; Dhami & Mumpower, 2018). Clearly, the value of each mode of cognition ought to be informed by what the individual is trying to achieve, i.e., accuracy with respect to some criterion or coherence with respect to some standard or policy.

The intelligence community has been heavily influenced by the position that intuition is a default mode of cognition that operates when the more superior deliberative mode is unavailable (see Heuer, 1999). In addition, although accuracy is the desired goal in intelligence analysis, analytic tasks are characterized by uncertainty that cannot easily be reduced. Relevant data may be missing and unreliable (as well as intentionally deceptive), data collection may be biased, and obtaining valid, reliable and timely outcome feedback is extremely difficult. Thus, the intelligence community has developed policies for practice in the hope that these will increase accuracy. Indeed, in their efforts to encourage analysts to adopt deliberative thinking, intelligence organizations train analysts in critical thinking skills including logic as well as in the application of so-called ‘structured analytic techniques’ that typically involve the application of specific rules in a sequential process (e.g., Advanced Technical Intelligence Center, 2014; Intelligence and Security Academy, 2014; Office of the Director of National Intelligence, 2007; UK Ministry of Defence, 2013; US Government, 2009; see also Dhami, Belton, & Careless, 2016).

Nevertheless, as Heuer and Pherson (2008) highlight, rather than applying critical thinking, analysts may opt for a narrow and sometimes inappropriate range of strategies. These might be strategies they learned during their formal education; those that are readily available to them; those which save time; and those driven by readily available data (even if it is not pertinent to solving the task at hand). It is argued that the use of such strategies is likely to lead to biased and erroneous conclusions, which can potentially misinform decision-makers. In addition, there may be negative resource costs of ineffective working practices.

In the present paper, we examine analysts' reported use of strategies classed as involving more or less critical thinking (i.e., deliberative or intuitive) in an effort to better understand how analysts work, and to contribute to the small, but growing body of extant research on intelligence analysis. There is a general dearth of empirical research in this domain, which not only limits our understanding of an important area of applied cognitive psychology, but which also thwarts efforts to strive for an evidence-based approach to the training and assessment of analysts (see Dhami, Mandel, Mellers, & Tetlock, 2015).

Past Research on Analysts' Working Practices

To date, only a handful of studies have attempted to describe the analytic strategies used by intelligence analysts. Pirolli, Lee and Card (2004, see also Pirolli and Card, 2005) studied two analysts with over 20 years' experience each. The analysts completed a simulated problem of their choice using open source data, while using a think-aloud protocol (i.e., self-reporting their reasoning while performing a task). They spent most of their time finding information, extracting it, and making basic inferences about patterns in the data.

Trent, Voshell and Patterson (2007) observed four groups of 10 military analysts with on average four years' experience, completing a task during a five-day training exercise. The groups provided daily briefs and were assessed based on whether they arrived at a preferred conclusion and if this was conveyed with sufficient analytic rigor. The two 'successful' groups had arranged their workspace to allow for maximum interaction between members and shared their thinking by adding relevant dates to a wall-sized calendar. At times, all teams had either dedicated too much time to performing individual (cognitive) tasks and not enough to collaboration or vice, versa. None of the groups used a structured approach to hypothesis testing and instead preferred a narrative approach.

Chin, Kuchar, and Wolf (2009) studied five experienced analysts working on two hypothetical scenarios involving individual and collaborative analysis, respectively. Analysts had to write and present a report. It was found that analysts organized the information, and highlighted and extracted facts. However, analysts' judgments of the credibility of information and sources were subjective and depended on their experiences. Analysts also relied on personal knowledge when attempting to identify patterns and trends in the data. They shifted into new lines of queries and investigations before eventually converging on a coherent story. Analysts said they would abandon a systematic approach to analysis when working under time pressure. Collaboration enabled analysts to devote more time to resolving discrepancies in the data.

In Patterson, Roth and Woods' (2001) study, 10 analysts with seven to 30 years' experience were presented with a simulated problem based on a real past event. They had access to a database of 2,000 (mostly relevant) text documents. Analysts used a think-aloud protocol to describe how they would analyze the data. Data from two analysts could not be examined, but the remainder narrowed down the dataset using basic queries and browsing the dates and titles of the documents. They opened from four to 29 documents and selected one to four 'key' documents, and searched for corroboration and information that resolved discrepancies, in an effort to synthesize the data into a coherent story. Consequently, analysts missed highly relevant data. Half of the analysts used 'high-profit' documents – they spent more time on analysis and read more documents. This did not result in more accurate statements, although it did lead to fewer inaccurate statements. Inaccurate statements were based on default assumptions and incorrect or out-of-date information.

Roth et al. (2010, Study 2) studied six analysts with eight or more years' experience over a four-day period, as they responded to six information requests associated with the same hypothetical problem. Analysts performed some tasks using a prototype decision aid and other tasks unaided. Data was collected using a think-aloud protocol. Analysts used several strategies including expanding and reframing the request (e.g., by including pre- and post-conditions and implied questions, and removing restrictive assumptions). They also used meta-information to guide selection of collection assets (e.g., tolerance for instability of information over time, and time taken to analyze and integrate new information). In addition, analysts used contextual cues to assess their confidence in being able to respond to the request in time, and these contextual cues included the complexity of the search space, the redundancy and diversity of sources and the need to coordinate across organizations. Thus, these analysts actively engaged in problem reformulation and demonstrated awareness of some of the factors that may affect their analysis.

Finally, Dhami and Careless (2015a) conducted an experiment involving 15 analysts with on average eight years' experience, who were divided into three groups. The analysts had to produce a written report after performing a representative task. Two groups worked collaboratively (i.e., distributed or co-located) and one group worked individually. Analysts had access to 29 documents: about a third did not contain any useful intelligence, the rest contained key intelligence and/or corroborative information, and a few were in a foreign language. The researchers measured the quality of the reports as well as the accuracy of the conclusions drawn. It was found that analysts working individually produced better quality reports measured on a number of criteria (e.g., descriptive analysis, analytic filtering, and communicating analysis) than those working collaboratively. In all reports, descriptive analysis was strong but there was a lack of critical thinking. None of the reports contained accurate conclusions. The three groups differed in how they structured their activities. For instance, the co-located group divided information across individuals in the team according to their expertise. Everyone in the distributed group skimmed through all of the documents before dividing them amongst members. Those working individually read all of the documents, summarizing, grouping and prioritizing them, drawing hypotheses and testing them, before deciding on next steps.

In sum, it is difficult to paint a clear picture of how experienced analysts work. This is partly because different studies focused on different stages of the analytic workflow, with only one examining all stages (Dhami & Careless, 2015a). The sorts of cognitive and practical skills that can be useful at each stage may differ. For example, 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, whereas 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. Past research also does not distinguish, a priori, between strategies involving more or less critical thinking (deliberation versus intuition), thus rendering the evaluation of analytic practices as somewhat post hoc. Problematically, past research has involved qualitative methods and small samples of analysts thus rendering the findings unreliable and lacking in generalizability. Finally, no-one has systematically explored how the strategies that analysts may use are associated with their training and experiences. This information can be used to assess the effectiveness of analytic training and identify the sorts of experiences that promote or hinder a deliberative approach to analysis.

The Present Research

The primary goal was to measure how often analysts report using 'deliberative' and 'intuitive' strategies when solving specific tasks at each stage of the analytic workflow. There is insufficient past research to draw a priori predictions about the frequency of analysts' use of such strategies at specific stages of the workflow. In order to overcome some of the shortcomings of past research, we sampled a large number of analysts, classed strategies a priori as involving more or less critical thinking, and examined each stage of the workflow.

A secondary goal was to explore the association between how often analysts said they would apply a particular class of strategy and the number of years they had worked in the intelligence community, their analytic skill level, whether or not they had completed analytic thinking training, and the proportion of time they spent working collaboratively (opposed to individually).

In terms of the relationship between analytic experience and strategy use, contrasting views on intuitive and deliberative thinking would lead us to make different predictions. For instance, whereas some believe that expertise leads to greater use of intuitive thinking (e.g., Klein, 1989; see also Klein, 2008; Hammond, 1996; 2000; 2010), others suggest this mode of cognition is indicative of less expertise (e.g., Tversky & Kahneman, 1974; see also Kahneman, 2011; Kahneman & Klein, 2009). However, as we mention earlier, characteristics of the intelligence domain such as the degree of uncertainty and lack of feedback may make it difficult to develop expertise (see also Harvey, 2011). In addition, the fact that intelligence organizations train their analysts to apply critical thinking and structured analytic techniques means that we would predict a positive relationship between years of experience working in the intelligence community and use of deliberative strategies, and a negative relationship between experience and the use of intuitive strategies.

Intelligence organizations typically assess the skill level of their analysts in performing specific analytic tasks (e.g., writing reports, using geospatial technology). It would be reasonable to hypothesize that a higher overall skill level would be positively associated with the use of deliberative strategies and negatively associated with the use of intuitive strategies.

Similarly, given that analytic thinking training typically includes teaching critical thinking skills and structured analytic techniques, it would be reasonable to hypothesize that analysts who have completed such training will report greater use of deliberative strategies and less use of intuitive ones compared to analysts who have not completed such training.

Finally, collaborative analysis is often encouraged because there is a belief that it helps to overcome the limitations of individual analysis (see e.g., Cooper, 2005). Past studies on collaborative versus individual analysis, however, report mixed findings as to the respective benefits of these two ways of working (e.g., Convertino, Billman, Pirolli, Massar, & Shrager, 2008; Dhami & Careless, 2015a; Woolley, Gerbasi, Chabris, Kosslyn, & Hackman, 2008). Some psychological research suggests that collaborative working can lead to cognitive loafing (Weldon & Gargano, 1985; 1988). Nevertheless, it is unclear how an analyst who spends the majority of his or time working collaboratively will be affected when working individually, and so we refrain from making a directional prediction with regard to the relationship between the extent of collaborative working and frequency of use of intuitive and deliberative strategies.

Method

Participants

A sample of 113 practicing intelligence analysts volunteered to participate in the research (details of their recruitment are provided in the procedure section below). These analysts answer strategic and tactical intelligence questions across a variety of domains such as counter-terrorism, nuclear non-proliferation and military. To do so, they draw upon both structured and unstructured data derived from a range of sources including publically available material.

Just over half (56.8%) of the sample were male. The mean age was 37.27 years (*SD* = 10.28). Nearly all (92.8%) were employed to work on a full-time basis. The sample reported having a mean of 5.18 years of experience (*SD* = 3.38) working in the intelligence community. The mean proportion of time analysts said they worked collaboratively/as part of a team was 35.68% (*SD* = 22.31). Analysts' overall skill level ranged from 0 to 53 (*M* = 17.86, *SD* = 9.08) as measured on a 0 to 84 scale used by the organization from which the sample was drawn.[1] Thirty-three percent said they had completed analytic thinking training.[2]

Survey

A survey was designed by a team of experienced analysts (including those with management duties) and analytic trainers in collaboration with the authors. We endeavored to ensure that the tasks along the analytic workflow were representative of those that may be conducted within the intelligence organization from which the participants were drawn.[3] The survey comprised four parts, two of which are relevant to the present research (and are available from the first author).[4]

One part of the survey elicited demographic information regarding participants' gender, age, work status, years of experience working in the intelligence community, proportion of time spent per week working collaboratively (as opposed to individually), skill level, and analytic thinking training.

The other part of the survey presented participants with six scenarios that each represented the six stages of the analytic workflow (i.e., capture requirements, plan analytic

[1] The organization rates analysts on 21 different analytical skills, and each one has five levels from zero to four.
[2] This involves learning critical thinking skills, structured analytic techniques and about cognitive biases.
[3] An early version of the survey was pilot tested on a sample of 60 analysts from the same organization (who did not participate in final data collection). This was primarily used to streamline the survey and clarify the wording of specific items.
[4] The other two parts examined how analysts would order an analytic workflow and their preferred thinking style, and some of the findings are reported in Dhami and Careless (2015b).

response, obtain data, process data, interpret outputs, and communicate conclusions, see Dhami & Careless, 2015b). Each scenario referred to a different intelligence problem and so there were no dependencies across stages. For example, Scenario 5 referred to the interpret outputs stage of the workflow. Participants were told: “You have just gained a memory stick which was seized from one of your key suspects during the arrest of his associate. It holds a massive amount of data. You think the suspect is involved in money laundering which is ultimately used to fund illegal businesses. There is some reporting which confirms this, however, the source is new and un-validated. You have so far only been able to find very scarce other information on the suspect which mostly consists of SMS and occasional email. You have never been able to establish the topics of these conversations and think they are coded. As you have been unable to find enough evidence to validate your money laundering hypothesis you are due to be moved off onto another investigation in one week’s time, unless the new data sheds more light on the situation.”

For each scenario, participants were asked: “In this situation, how often do you do the following things?” They were then presented with four alternative strategies that could be used for solving each task.[5] Two of these were a priori classed as involving more or less critical thinking (i.e., deliberative or intuitive), although participants were not told this. The strategies classed as ‘intuitive’ were ones that experienced analysts (including those with management duties) and analytic trainers believed that analysts may opt for if they had less training, skills and experience, and wanted to reduce effort. By contrast, the strategies classed as ‘deliberative’ were ones that analysts may opt for if they had more training, skills and experience, and were willing to expend more effort. For example, the strategies presented with Scenario 5 were: (1) “Systematically look through all the data retrieved, summarizing the key points as you go.” (2)

[5] At the end of this part of the survey, participants also had an opportunity to provide additional responses by reporting any other strategies that they may use, however, few did so.

"Search for data that will specifically corroborate or disprove any of your hypotheses about the situation." (3) "Map the relationships between the key points, making a distinction between facts and hypotheses." (4) Quickly try and determine the 'story' behind the data and find information to corroborate this." Here, strategies (1) and (4) were classed as intuitive and (2) and (3) as deliberative. Participants provided a rating for each strategy on a 5-point scale labelled at each point (i.e., 1 = "never", 2 = "a little", 3 = "some", 4 = "a lot", and 5 = "always").

Procedure

Analysts were recruited via advertisements on the intranet of a UK intelligence organization. These adverts stated that the research was led and designed by a non-employee. Analysts were informed that participation was voluntary and anonymous. The survey was available online for a two-week period on the intelligence organization's intranet, and participants completed the survey during their normal workday.

Analysis and Findings

The data analysis and findings are presented below in relation to the two main goals of the present research described earlier.

Analysts' Strategy Use

The primary goal was to examine how often analysts said they would use strategies classed as 'intuitive' and 'deliberative' when solving tasks along each stage of the analytic workflow. Figure 1 presents the means (and standard deviations) of the frequency with which analysts said they would apply each class of strategy along each stage of the workflow. For simplicity, the responses to the two strategies classed as intuitive at each stage were averaged, as were the responses to the two strategies classed as deliberative. Higher scores indicate more frequent application of a strategy.

FIGURE 1 ABOUT HERE

In order to determine if there were any statistically significant differences in the mean frequency with which analysts said they would apply each class of strategy, we computed paired samples *t*-tests for each stage of the workflow.[6] There were no significant differences observed at the plan analytic response stage ($t[112] = 0.22$, $p = .826$, $d = .02$), obtain data stage ($t[112] = 1.37$, $p = .173$, $d = .13$) and interpret outputs stage ($t[112] = 1.38$, $p = .170$, $d = -.13$). Here, analysts said they would apply deliberative strategies as often as intuitive ones.

However, there was a statistically significant difference in the reported frequency of application of intuitive versus deliberative strategies at the process data stage ($t[112] = 7.88$, $p < .001$, $d = -.74$) and communicate conclusions stage ($t[112] = 11.43$, $p < .001$, $d = -1.07$). The difference was marginally significant at the capture requirements stage ($t[112] = 1.87$, $p = .064$, $d = -.17$). As Figure 1 shows, analysts said they would apply deliberative strategies more frequently than intuitive strategies when capturing requirements, processing data and communicating conclusions.

Strategy Use and Analysts' Experiences, Skills and Training

A secondary goal of the present research was to explore the association between how often analysts said they would apply each class of strategy and their years of experience working in the intelligence community, skill level, analytic thinking training, and the proportion of time they spent working collaboratively.

Pearson's correlation coefficients were computed between the number of years that analysts had worked in the intelligence community and how often they said they would apply

[6] These tests were two-tailed, and a Bonferroni correction was applied to the alpha level.

each class of strategy at each stage of the workflow.[7] None of these correlations were statistically significant (*r*s excluding sign ranged from .02 to .13, *p*s > .05, *n*s = 111).

Pearson's correlations were also computed between analysts' overall skill level and how often they said they would use each class of strategy at each stage of the workflow.[8] The correlations (excluding sign) ranged from .32 to .23 (*n*s = 111), and all but one were non-significant (*p*s > .05). For the one statistically significant correlation, we found that contrary to the prediction, there was a significant positive relationship between overall skill level and use of an intuitive strategy at the communicate conclusions stage ($r = .23$, $p = .015$).

Table 1 presents the means and standard deviations of the reported frequency of use of each class of strategy at each stage of the workflow by whether or not analysts had completed analytic thinking training. With one exception, independent samples *t*-tests revealed no statistically significant differences in how often analysts with and without analytic thinking training said they would apply each class of strategy at most of the stages of the workflow.[9] For the one exception, there was a significant difference in the reported use of deliberative strategies at the communicate conclusions stage ($t[111] = 1.68$, $p = .048$). As Table 1 shows, and in line with the prediction, compared to their counterparts who had not completed analytic thinking training, those who had, reported greater frequency of using deliberative strategies at this stage.

TABLE 1 ABOUT HERE

Finally, correlations were also computed between the proportion of time (per week) that analysts spent working collaboratively, and how often they said they would use each class of strategy at each stage of the workflow.[10] The correlations (excluding sign) ranged from .02 to .29

[7] These tests were one-tailed.
[8] These tests were one-tailed.
[9] These tests were one-tailed.
[10] These tests were two-tailed.

(*n*s = 111), and all but two were non-significant (*p*s > .05). For these two, there was a significant positive relationship between time spent working collaboratively and use of a deliberative strategy at the plan analytic response stage ($r = .29$, $p = .002$), and the use of an intuitive strategy at the obtain data stage ($r = .24$, $p = .011$).

Discussion

Although analysts are expected to approach analytic tasks with a critical mindset, there is a dearth of empirical research on how analysts do their work. The small body of extant research employs qualitative, concurrent or retrospective self-report methods to examine how small samples of experienced analysts work at specific stages of the analytic workflow (Chin et al., 2009; Dhami & Careless, 2015a; Patterson et al., 2001; Pirolli et al., 2004; Pirolli & Card, 2005; Roth et al., 2010; Trent et al., 2007). Thus, much of what we know about how analysts do their work comes from post hoc investigations into intelligence failures (e.g., Butler, Chilcot, Peter, Mates, Taylor, 2004; Pfeiffer, 1984). However, the generalizability of their findings can be extremely limited. The present research aimed to shed more light on analytic practices by using a quantitative method to examine how often a large sample of analysts said they would apply strategies classed as ‘deliberative’ and ‘intuitive’ to solving (independent) problems, at each stage of the analytic workflow. In addition, we explored factors that may be associated with the application of each class of strategy.

Although we attempted to overcome some of the shortcomings of past research, some limitations remain. The primary one is the reliance on self-report data. In using a retrospective self-report method we avoided concerns relating to concurrent self-report (think-aloud) methods, namely that they may interfere with the processes being studied and that they face the challenges associated with introspecting and articulating cognitive processes (Nisbett & Wilson, 1977;

Russo, Johnson, & Stephens, 1989). However, our method is potentially problematic due to difficulties in recall (Nisbett & Wilson, 1977) and the opportunities it affords for social desirability response bias (Paulhus, 1991). These concerns are somewhat muted by the fact that analysts were asked to recall strategies they use for tasks they perform on a daily basis, and any response bias would likely manifest in reports of greater use of deliberative rather than intuitive strategies, which did not occur. In addition, one could argue that our method is akin to that used by intelligence organizations themselves, who typically assess the quality of the analytic process based on analysts' reports of how they arrived at a specific conclusion. Nevertheless, future research should use a mixed methods design whereby self-report data is triangulated with behavioral data (e.g., from controlled experiments, observations, intelligence reports). Bearing this limitation in mind, below we summarize and discuss the present findings.

Deliberation versus Intuition

Analysts said they would use deliberative strategies more often than intuitive ones at the initial and final stages of the workflow. This is compatible with studies suggesting that analysts try to grasp the operational aim and context before starting their work (Dhami & Careless, 2015a), and that they may expand and reframe the question (Roth et al., 2010). The findings are also consistent with Dhami and Careless (2015a) who reported that analysts aim to communicate/present their analysis in a clear and meaningful way, highlighting areas of uncertainty, and distinguishing between objective fact and subjective judgment. Most intelligence organizations place considerable value on customer engagement and satisfaction, and intelligence products represent a tangible output of analytic work. The present findings suggest that analysts may actively consider the question posed in order to produce reports that are customer-focused.

Analysts also said they would use deliberative strategies more often than intuitive ones at the processing data stage. This contrasts with studies suggesting that analysts perform routine and simple operations on data, looking for basic patterns (Chin et al., 2009; Patterson et al., 2001; Pirolli & Card, 2004). It is unclear to what extent methodological differences can explain the disparity in findings as past studies have used think-aloud protocols whereas we used a survey method eliciting self-reports of how analysts say they perform a task. The fact is that intelligence organizations often invest heavily in developing tradecraft, tools and technology, and so it may not be surprising that, as we find, analysts use more critical thinking at this stage of the workflow.

There was no significant difference in how often analysts said they would use intuitive and deliberative strategies at the plan analytic response, obtain data and interpret outputs stages of the workflow. The preference for approaching analytic tasks in a routine manner means that analysts may not adapt sufficiently to emerging analytic problems (i.e., those that require different/new working practices) and they may spend too much of their limited time wading through data. Past research suggests that although analysts may consider some of the factors that might affect their ability to respond to an intelligence question (Roth et al., 2010); they may also ignore potentially relevant data (Patterson et al., 2001; Pirolli & Card, 2004); and may rely on subjective interpretations of the data, seeking to confirm their ideas (Chin et al., 2009; Patterson et al., 2001; Pirolli & Card, 2004; Trent et al., 2007). Intelligence organizations could place greater emphasis on training analysts to carefully plan their analytic response, as well as freeing analysts' time by automating information searches where possible, and supporting critical thinking via a combination of training and technology.

These latter set of findings also suggest that future research could also explore Hammond's (1996) assertion that intelligence analysis requires the use of both System 2 (deliberative) and System 1 (intuitive) thinking. According to Hammond's (1996; 2000; 2010; see also Dhami & Thomson, 2012) cognitive continuum theory, cognition moves along a continuum from System 1 to System 2. Quasirationality lies in-between and refers to a combination of intuitive and deliberative thinking. Thus, sometimes an analyst may use more intuition than deliberation, other times she may use more deliberation than intuition, and at other times the use of these two modes of cognition may be equal. The present research did not examine quasirational strategies, and in fact, the operationalization of intuitive and deliberative strategies was quite broad. Future research is warranted to examine the extent to which analysts apply more precisely specified strategies that are wholly deliberative, wholly intuitive or quasirational (a combination of both deliberation and intuition) strategies when solving tasks along the analytic workflow.

Future research could also examine other propositions in Hammond's theory in order to develop a more nuanced understanding of best working practices in intelligence analysis.[11] Hammond (1996, 2000) proposed that the mode of cognition used is induced by properties of the task. For instance, tasks characterized by a large amount of information, containing some redundancy and requiring subjective interpretation would induce intuitive thinking (see also Patterson, 2017). By contrast, tasks involving less information, with less redundancy and requiring objective interpretation would induce deliberative thinking. Tasks such as intelligence analysis that comprise a combination of properties inducing intuitive and deliberative thinking

[11] There is psychological evidence to support the propositions made by Hammond's theory (Dunwoody, Haarbauer, Mahan, Marino, & Chu-Chun, 2000; Horstmann, Ahlgrimm, & Glöckner, 2009; Hamm, 1988; Hammond, Hamm, Grassia, & Pearson, 1987; Mahan, 1994; Marewski & Mehlhorn, 2011; Rusou, Zakay, & Usher, 2013; Seifert & Hadida, 2013).

would induce quasirationality. In addition, Hammond suggested that the upper level of cognitive performance is dictated by the match between properties of the task and mode of cognition. Thus, deliberative thinking alone may be neither necessary nor sufficient for ceiling-level performance, and in fact, quasirational (or even intuitive) thinking may produce better performance (and outcomes) under certain conditions. An understanding of the effects of the correspondence between cognitive mode and task properties in the intelligence analysis domain can be useful in helping to infer the potential accuracy of intelligence products, which is important given the challenges associated with obtaining outcome feedback in this domain.

Analytic Experiences, Skills and Training

The present research also explored the relationship between how often analysts said they would use intuitive versus deliberative strategies and their experiences, skills and training. This included an exploration of the relationship between the number of years analysts had worked in the intelligence community and their reported frequency of strategy use. There was little evidence of a relationship between these two variables. The small sample sizes used in past research has precluded direct comparisons of more and less experienced analysts, however, the literature we reviewed earlier suggests that experienced analysts do not necessarily demonstrate more critical thinking in spite of the efforts made by intelligence organizations. Although the present study used a broad measure of experience (similar to past research), the findings we discuss below with regard to the relationship between reported strategy use and analysts' skill level and training suggest that it may be difficult for analysts to develop a degree of expertise that distinguishes between the working practices of more and less experienced analysts. Indeed, analysts may opt to develop skills and complete training at different points in their career meaning that these variables are not necessarily positively related to experience.

We did not find much evidence of a relationship between analysts' overall skill level and their reported strategy use. The skill levels measured by intelligence organizations typically reflect specific technical and tradecraft skills (e.g., writing reports, using geospatial technology). The disconnect between skill level and strategy use suggests that intelligence organizations may wish to reconfigure the concept of technical and tradecraft skill level within a broader cognitive framework for approaching analytic tasks. Indeed, some practical skills may require more (and similar) elements of deliberative thinking than others, and so these could be grouped together for both training and assessment purposes. Currently, training in specific technical and tradecraft skills is quite separate from training in analytic thinking skills, partly because the intelligence community has been slow in acknowledging that analysis is fundamentally a cognitive activity. We argue that instead of thinking skills being an 'add on' they should form a basis for the consideration of practical technical and tradecraft skills.

First, however, the intelligence community may wish to rethink the contents of its analytic thinking training. This is because we did not observe many systematic differences in reported strategy use amongst analysts who had completed analytic thinking training and their counterparts who had not. Analytic thinking training typically includes a focus on critical thinking and the use of specific analytic techniques (e.g., Office of the Director of National Intelligence, 2007; UK Ministry of Defence, 2013; US Government, 2009). However, there is no conceptual framework to tie these thinking skills together. There is also an overemphasis on cognitive bias, with few debiasing instructions beyond telling analysts to 'be aware of bias!' (see Belton & Dhami, in press). Future research could further explore reasons for the apparently limited benefits of analytic thinking training. Is such training potentially ineffective because: (a) The material is not sufficiently integrated into a useful cognitive framework? (b) Analysts do not fully understand the material being taught? (c) The training rarely puts the material in the context of performing specific sorts of analytic tasks along each stage of the workflow? (d) Analysts lack the ability to put their training into practice? (e) A combination of the aforementioned factors?

Finally, there is an increasing emphasis on collaborative analysis and this has led to a growing industry in collaborative analytic technologies. However, the trend has not been informed by any empirical evidence on the effectiveness of collaboration. We found no significant association between the proportion of time analysts spent per week working collaboratively (opposed to individually) and how frequently they said they would apply each class of strategy. Whereas collaborative working did not appear to have the deleterious effect on individual cognition that some have suggested (Weldon & Gargano, 1985; 1988), it also did not have a particularly beneficial impact on analysts' working practices as some believe (e.g., Hackman & Woolley, 2011). Some research suggests that the nature of the collaboration may be key to its potential success (e.g., Convertino et al., 2008; Dhami & Careless, 2015a; Woolley et al., 2008). Therefore, future research ought to use other measures of collaborative working (e.g., co-located v. distributed, diversity, role in a team, tasks performed collaboratively) before drawing any definite conclusions regarding the impact of collaboration. For now, our findings, along with those of some past research, suggest that the intelligence community's penchant for collaborative analysis may not be supported by the evidence.

Unfortunately, the policies and practices developed and promulgated by intelligence organizations tend not to be based on scientific theories, methods or research (see National Research Council, 2011; Pool, 2010). We believe that the intelligence community should adopt an evidence-based approach to training and assessing its analysts. As Dhami et al. (2015) point out, an evidence-based approach would not only address critics' concerns about the effectiveness of analytic practices, which could ultimately mitigate the risk of future intelligence failures, but such an approach could also strengthen the intelligence community's accountability processes. As the present study demonstrates, an evidence-based approach could borrow from theories and methods in the field of Decision Science specifically and cognitive psychology more generally.

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Table 1. Frequency of Application of Intuitive Versus Deliberative Strategies by Stages of the Analytic Workflow and Analysts' Analytic Thinking Training

		Training (*n* = 47)	No training (*n* = 66)
Stage of workflow	Strategy class	*M* frequency of application (*SD*)	*M* frequency of application (*SD*)
Capture requirements	Intuitive	3.88 (.70)	3.97 (.76)
	Deliberative	4.17 (.78)	4.03 (.84)
Plan analytic response	Intuitive	3.80 (.81)	4.01 (.97)
	Deliberative	3.88 (.54)	3.91 (.74)
Obtain data	Intuitive	3.82 (.62)	3.58 (.91)
	Deliberative	3.59 (.75)	3.55 (.89)
Process data	Intuitive	3.52 (.79)	3.30 (.75)
	Deliberative	3.97 (.58)	4.04 (.74)
Interpret outputs	Intuitive	3.52 (.87)	3.58 (.96)
	Deliberative	3.72 (.79)	3.61 (.92)
Communicate conclusions	Intuitive	2.24 (.79)	2.28 (1.03)
	Deliberative	3.88 (.87)	3.60 (.92)

Figure 1. Frequency of Application of Intuitive and Deliberative Strategies by Stages of the Analytic Workflow