

How Might “Transformational” Technologies and Concepts be Barriers to Sensemaking in Intelligence Analysis?

Brian M. Moon, M.Sc.

Klein Associates Inc
brian@decisionmaking.com

Robert R. Hoffman, Ph.D.

Institute for Human and Machine Cognition
rhoffman@ihmc.us

Abstract

The United States Intelligence Community has seen a number of calls for transformation in recent years. Many of the recommendations have drawn on common assumptions about the cognitive work of intelligence analysts (IA), not on empirical study of how they actually work. This paper reviews both the common assumptions and empirical examinations of IA, and highlights recent work focused on the macrocognitive function of sensemaking. Using Klein's Data/Frame Model of Sensemaking, we demonstrate via empirical examples how many of the technological and conceptual recommendations for change in the IC are proving to be barriers to sensemaking.

KEYWORDS

Sensemaking, intelligence analysis, macrocognition.

INTRODUCTION

Following the occurrence of several ‘errors’ and the uncovering of systematic ‘flaws’ (e.g., McGrody and Lin, 2004), the United States Intelligence Community (IC) believes it must seek fundamental, systematic change—a trumpet blown most recently by the Commission on the Intelligence Capabilities of the United States Regarding Weapons of Mass Destruction (WMD Commission):

“In short, to succeed in confronting today’s and tomorrow’s threats, the Intelligence Community must be transformed... demands of this new environment can only be met by broad and deep change in the Intelligence Community...”

The calls for reform strike across the board—from organizational realignments to training revisions to the increased use of technology—and derive, *ostensibly*, from an understanding of the way in which analysts go about their work. Many of the recommendations are not new. Nor have they been heeded by the notoriously resistant IC they were developed to serve:

“Indeed, commission after commission has identified some of the same fundamental failings we see in the Intelligence Community, usually to little effect.” (WMD Commission, 2005)

The recommendations, too, have driven much of the research and development (R&D) efforts underway across the IC, as the R&D community has scrambled to be responsive to the urgency of world events and the subsequent reform proposals.

In this paper we suggest that while change in the IC is certainly necessary (as it usually is for any other domain, organization, or community), many of the recommendations toward such change are themselves good candidates for revised thinking. They rest, perhaps unknowingly, on common assumptions about the cognitive work of intelligence analysts. While other authors have outlined the organizational and cultural aspects of resistance to change in the IC (see, for example, Johnston, 2005), our focus is on those recommendations that lay claim to transforming the cognitive work in intelligence analysis. We suggest that it is the persistent reliance on common assumptions about cognitive work—as opposed to a reliance on empirical research of how analysts *actually do work*—that is the primary cause for the limited success of the recommendations offered to the IC.

While admittedly not a systematic review of the entire landscape of the IC’s R&D community, we draw for our case on direct experience in evaluating technologies intended to improve the IC, input from a community of practice focused on cognitive systems engineering for the IC, some dozens of knowledge elicitation interviews with practicing and retired intelligence analysts, a review of a wide range of unclassified documentation, and a year-long naturalistic observation of

a laboratory chartered with intelligence transformation. We freely admit that our arguments are based on partial information, due in part to the classified nature of the IC. Nevertheless, our primary thesis is that many of the “transformational” technologies and concepts offered in recommended improvements to the IC can actually impede intelligence analysis—they have shown to be barriers to sensemaking. We shall demonstrate these by example in the second half of the paper. In order to provide the context for the necessity of the primary thesis, we begin this paper with our secondary thesis which is that the elements of the R&D community that focus on how analysts actually work (i.e., naturalistically-inspired study and application) face an uphill battle in steering reform. The IC by and large continues to focus its interests on R&D efforts toward answering to the common recommendations, which in turn are based on common assumptions about the cognitive work of intelligence analysts.

Secondary Thesis: Brief overview of research on cognition of intelligence analysis

Empirical research into the nature of intelligence analysis has been underway since at least the late 1970s. At that time, researchers sponsored by the US Army Research Institute for the Behavioral and Social Sciences (ARI) and the US Army Intelligence and Security Command (INSCOM), developed “a descriptive model of the cognitive processes involved in analysis” (Kater, Montgomery, and Thompson, 1979). Similar work continued during the 1980s, notably a continuation of ARI/INSCOM efforts that detailed the “cognitive bases of intelligence analysis” and offered textual and graphical representations of such, as seen in Figure 1 (Thompson, Hopf-Weichel, and Geiselman, 1984).

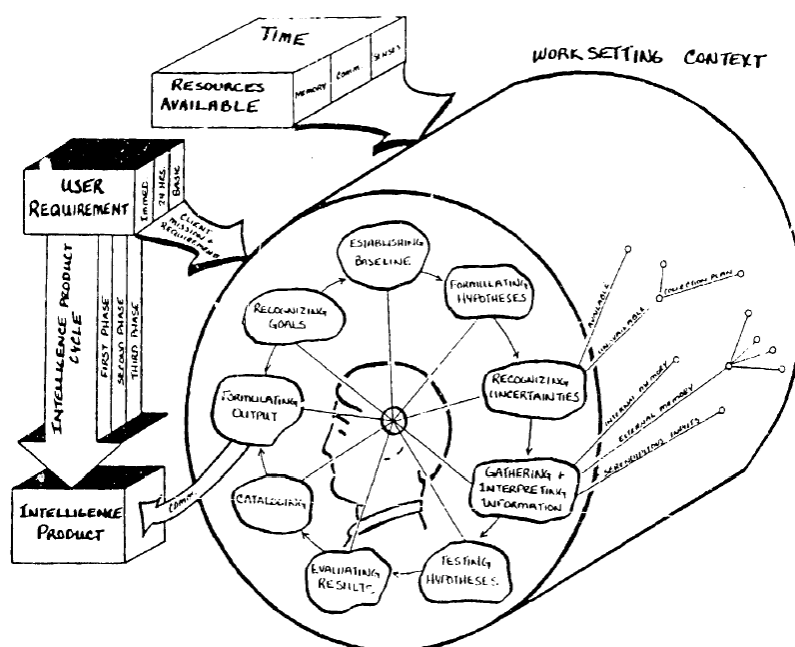


Figure 1. The cognitive basis of intelligence analysis, circa 1984.

Concerted efforts to study analysts appear to have abated from the mid-1980s until the late 1990s. The publication of Richards Heuer's *The Psychology of Intelligence Analysis* (1999) marked a resurgence of interest in the cognition of intelligence analysis, which continues today. Indeed, the IC and the Department of Defense have sponsored many efforts explicitly aimed at, *inter alia*, “infer[ring] the state of analysts and the analytic process from analysts’ activities” (see, for example, http://www.ic-arda.org/Novel_Intelligence/), anthropologically-based needs analysis (see Johnston, 2005), a number of small scale cognitive task analyses (see, for example, Klein, 2001, Hutchins, 2003, Pirolli et.al, 2004), simulation studies (see Patterson et al., 1999), and limited objective experiments with analytic methods (see Cheikes and Taylor, 2003) and (Cheikes, Brown, Lehner and Adlerman, 2004).¹

¹ An enhanced (but partial) bibliography of the research can be found at <http://cse1.eng.ohio-state.edu/foic/Enhanced%20Bibliography.html> (see the authors for access).

Speaking broadly and historically, the IC's R&D community has seen waves move across its surface, waves that notably follow the wider scene in cognitive psychology. The early research reflected an information processing theoretical base. Later came a wave of heuristics and biases research. Most recently, some of the research activity indicates Naturalistic Decision Making (NDM) perspectives. Yet, despite their parochial differences, several constants have emerged across the corpus of research. Thompson (1984) captured these succinctly:

- intelligence analysis is predominately concept-driven rather than data-driven;
- highly experienced and effective analysts
 - often appear to organize [their] knowledge around conceptual models
 - do not have access to more or better information than the less able analyst, but are better able to chunk the available items of information into significant wholes;
- bigger and better information collections systems do not necessarily result in better analysis; and
- many of the problems (technological) systems have experienced in the area of user acceptability appear to be traceable to the lack of understanding of the human performance aspects of intelligence analysis on the part of the system developers.

Even with the similarities in major themes of these research lines, however, several key figures have noted the continued absence of a grounded, empirically-based understanding of the individual and team cognitive processes inherent in intelligence analysis. Johnston, (2005) noted recently:

“[It] is not to say that an intelligence literature does not exist but rather that the literature that does exist has been focused to a greater extent on case studies than on the actual process of intelligence analysis...The problem is that most of the internal research has concentrated on historical case studies and the development of technological innovations. What is missing is focused study of human performance within the analytic components of the Intelligence Community. Questions about the psychology and basic cognitive aptitude of intelligence analysts, the effectiveness of any analytic method, the effectiveness of training interventions, group processes versus individual processes, environmental conditions, and cultural-organizational effects need to be addressed.”

Metaphors, Analogies, and Microcognition

These waves of empirical research have crashed into steep cliffs of metaphor, analogy and microcognition. Throughout the literature, conferences, and exhibition halls, intelligence analysis is compared to other intellectual enterprises, and analysts' work is captured with visual references. To name just a few, analysts are said to:

- connect the dots (between entities and events);
- find the needle (of important data) in the haystack (of available data);
- separate the wheat (credible data) from the chaff (of deceptive data); and
- put together the pieces of the puzzle (to form a complete picture), even when you see only the back of the puzzle and you are not given any of the edges.

Their work is often compared to scientists (see Johnston, 2005 and Heuer, 1999), medical diagnosticians (see Marrin and Clemente, 2005) medical generalists (see Mihelic, 2005), journalists (Agrill, 2002), and rhetoricists (Mills., 2003).

Closely related to the metaphors and analogies are a class of characterizations of analytic work that seemingly rest on empirical findings but rarely offer evidence of their veracity. These catch-phrases hint at aspects of analysis—particularly at challenging aspects—but by themselves seem to beg the question of their own importance. Thus, the literature is littered with calls to help analysts “flip the bathtub curve of time spent researching, analyzing, and producing” analytic products, “overcome biases,” and find “novel intelligence in massive data.” Rarely is a corresponding description of such challenges *as faced by intelligence analysts* offered.²

That these loose-fitting comparisons and generalizations have held back the waves of empirical research from having an impact on the recommendations put to the IC seems remarkable. However, in some cases the waves have actually served

² In noting the need “develop useful and valid metrics and measures that may be used to assess the impact of software tools and products intended to improve [intelligence analysis] performance,” Greitzer (2005) has also called attention to the under specification of “the difficulty or complexity of intelligence analysis tasks...” While his work goes far in delineating variables of difficulty, he also notes the continued necessity for “cognitive task analyses” and “cognitive models” to “add more detail” about how cognitive processes and how intelligence analysts use tools.

to fortify the walls. Heuer's *The Psychology of Intelligence Analysis*, with its primary focus on the cognitive biases realized in a laboratory research paradigm (i.e., microcognitive)—and with less emphasis on intelligence analysts and more on college students performing artificial tasks in artificial settings (see Hoffman, 2005), is a key example. As is shown below, more recent research has perpetuated the focus on the harm in cognitive biases and the need to overcome them.

Thus, the global situation can be represented as such:

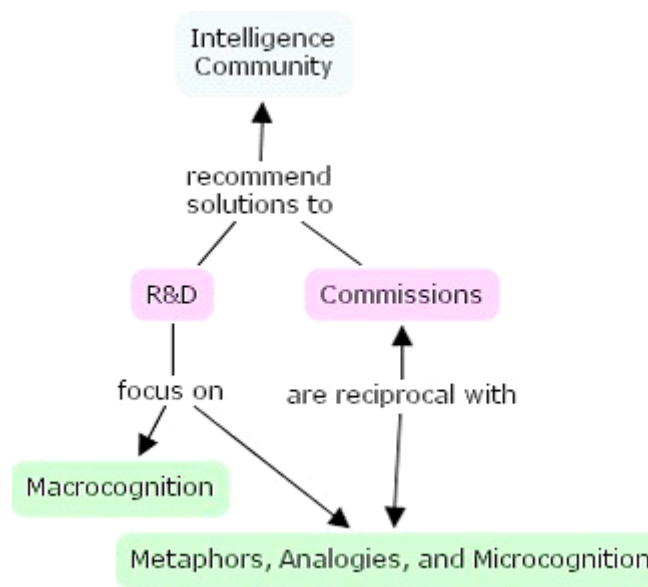


Figure 2. Concept map of the global situation

In this circumstance, the chips are stacked against the R&D members focused on how analysts *actually* work. Thus, it is not surprising that “questions about the psychology of intelligence analysts... [continue to need] to be addressed.” We would go further and suggest that what needs to be addressed is the macrocognition of intelligence analysis—the study of intelligence analysis as it actually occurs in its naturalistic settings. We have proposed macrocognition as the appropriate grain of analysis for cognitive work in context (Klein et al., 2003). Within the framework of macrocognition, the concept of sensemaking has provided an entry point for examining intelligence analysis.

Sensemaking

A number of researchers have cast their explorations of intelligence analysis in terms of sensemaking. The work ranges from modeling intelligence analysis, creating technology supports based on generic models of sensemaking, evaluating visualization tools and techniques, and describing the functions of sensemaking. Some have found in their work, a la the microcognitive approaches, evidence of biases and limitations needing corrections. Others have attempted to understand how sensemaking happens in situ.

As shown in Figure 3, Pirolli and Card (2005b) present an end-to-end model of intelligence analysis, broken into two major loops – foraging and sensemaking. Their analysis suggested that top down and bottom-up processes are invoked by intelligence analysts in an “opportunistic mix... [while many] of the leverage points...associated with the sensemaking loop concern problem structuring (the generation, exploration, and management of hypotheses), evidentiary reasoning (marshalling evidence to support or disconfirm hypotheses), and decision making (choosing a prediction or course of action from the set of alternatives).” Yet each of these leverage points can, they posit, be points of failure given three commonly known cognitive biases: span of attention for evidence and hypotheses, (lack of) generation of alternative hypotheses, and confirmation bias.

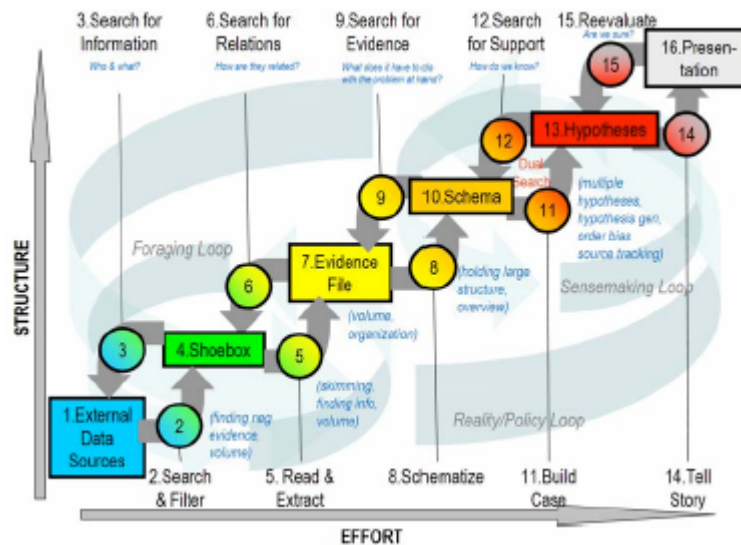


Figure 3. Pirolli and Card's model of intelligence analysis

Eggleston and Mostashfi (2005) proposed the development of a “Sensemaking Support Environment: A Thinking Aid for All-Source Intelligence Analysis Work.” Their work focused on overcoming analysts’ “inability to remember and recall critical information over long periods of time, inability to look at information from multiple perspectives, and inability to ‘share’ context in a collaborative manner.”

Kent Myers (2004) sought to apply Weick’s five mechanisms for reducing uncertainty as a means to ensure the “recovery of sensemaking in a world of computers.” By breaking down the analytic task by triangulating (reading highly varied sources of evidence that describe a situation or event), affiliating (seeing what others are seeing or constructing), deliberating (connecting a series of observations and mindful activities), consolidating (establishing context and creating patterns), and effectuating (taking action that creates reactions that are a source of learning), Myers developed a series of design recommendations for capabilities to support analysis. These included merging multiple sources at the user’s desk, filtering for lower false positives and for novel linkages, staging materials in context for later disposition, enabling implicit, tentative, and contradictory links and annotations, providing for perspective switching from frame to data, and creating pervasive collaboration opportunities.

While not explicitly concerned with ‘sensemaking,’ Elm and Woods (2003) have proposed a framework for evaluating proposed supports to intelligence analysis. Their basic insight is that success in analysis work is a process of convergence, while the risk is premature narrowing. The framework has three generic processes: down collect, that identifies potential relevant source material, conflict and corroboration that develops a set of findings to be explained, and hypothesis exploration that develops a coherent explanatory story that accounts for the findings. In between the support functions for these processes are phases of broadening checks. Successive cycles of narrowing and broadening produce convergence and avoid premature narrowing. Thus, similar to Pirolli and Card, their convergence model views sensemaking in analysis as a continual bottom up / top down process.

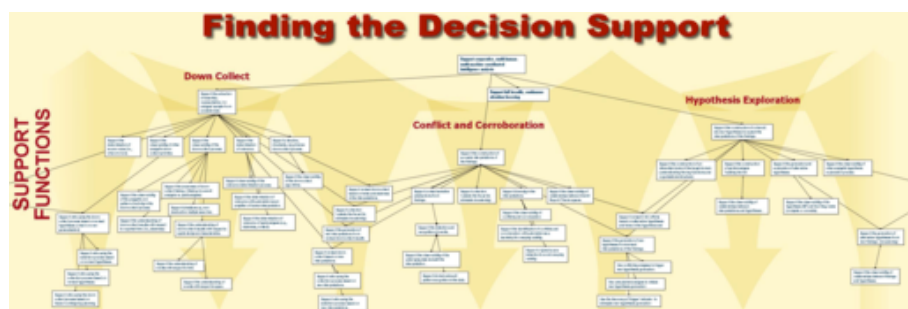


Figure 4. Elm and Woods’ “Finding the Decision Support / Convergence”

In keeping with the symbiotic process approach, Klein (2004) have proposed a ‘data/frame’ model of the nature of sensemaking activities, defining sensemaking as “the deliberate effort to understand events.” The model, shown in graphic form in Figure 4, also describes how sensemaking activities can result in a faulty account of events.

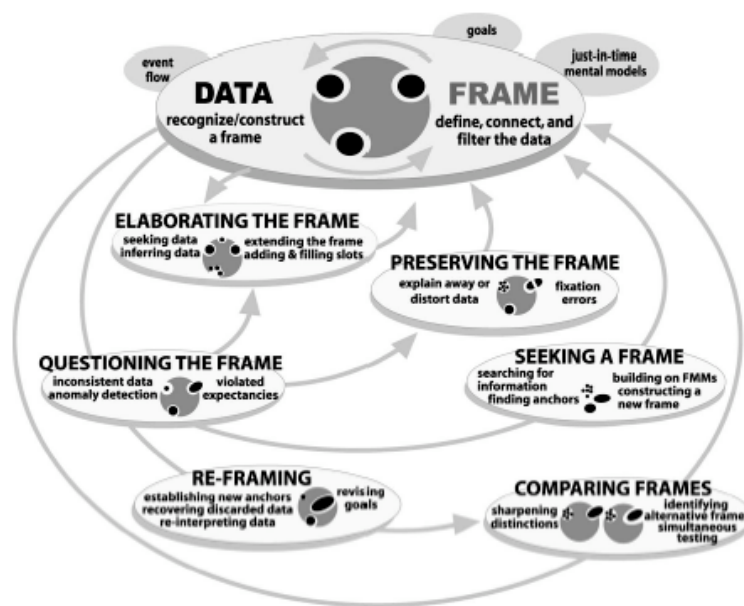


Figure 5. Klein's Data/Frame Model of Sensemaking

Unfortunately, space does not permit a comparison of each of these models in depth. Such an analysis would reveal glaring differences between the models, not the least of which is the perspective each provides on “bias”—Pirolli and Card, and Eggleston and Mostashfi view bias as a limitation to be overcome, whereas the others seek to understand and amplify sensemaking as it occurs. Because it seeks to explain breakdowns in sensemaking with reference to the functions of sensemaking—as opposed to bias-citing, Klein’s descriptive model goes the furthest in offering a set of findings useful for exploring the barriers to sensemaking seen in “transformational” concepts and technologies.

Primary Thesis: Barriers to Sensemaking

Derived from the Data/Frame Model of Sensemaking, Klein (2004) offered five common assumptions about sensemaking:

1. People should be encouraged to make only inferences that are logically valid;
2. Sensemaking builds up from data to produce a story;
3. People should avoid premature consideration of a hypothesis;
4. (*Experts and novices have different reasoning strategies*); and
5. More data leads to better sensemaking.

Somewhat unfortunately, several of them harken back to the themes in the cognitive research first voiced in 1984. We have found four of these common assumptions continually repeated throughout the “transformational” recommendations offered to the IC. This is not to say that many of the recommendations offered (in some cases over and over) to the IC are without merit. We recognize the cognitive work occurs within organizational constraints that can be particularly severe within the IC (e.g., security issues), and that many recommendations have sought to focus on relaxing or revising some of these. Our focus is on those recommendations that reflect some notion of the *cognitive work* inherent in intelligence analysis. Exemplars of several next follow. We first offer a “**Commission**” finding as an exemplar of how commissions state them. Next is a “**Concept**” description, which represents how the assumption is characterized in a program, analytic method, or technology concept. Finally, we present a generic³ example of a “**Technology**” that embodies the assumption.

Following each assumption, we provide counterfactuals to it in order to demonstrate *how the assumption actually impedes intelligence analysis*. Counterfactuals #1 arise from Klein’s theoretical Data/Frame Model of Sensemaking (and

³ The technology examples use language from actual technologies; however, specific references to the technologies and vendors have been extracted.

related research); Counterfactuals #2 arise from empirical research *conducted with experienced intelligence analysts* on how people have attempted to use recommendations.

Assumption #1. People should be encouraged to make only inferences that are logically valid.

- **Commission:** “A common theme from our case studies is that the fundamental logical and analytic principles that should be utilized in building intelligence assessments are often inadequately applied.” (WMD Commission, 2005)
- **Concept:** Structured Argumentation (SA)—Intelligence analysis, particularly “all-source analysis” that draws on all intelligence disciplines (e.g., signals intelligence, imagery intelligence, and human intelligence), is fundamentally a process of formulating *arguments* for intelligence *claims* or *conclusions*. An argument is a piece of discourse that presents: (1) an assertion; (2) statements of fact and/or opinion related to the assertion; (3) logical reasoning connecting the statements to the assertion; (4) a conclusion on the validity of the assertion. Structured argumentation refers to techniques for conducting the argument-forming portion of intelligence analysis more explicitly, typically through the use of specially-designed software applications (Cheikes and Taylor, 2003).

Technology: “Technology is a software tool developed for intelligence analysts that records analytic reasoning and methods, that supports collaborative analysis across contemporary and historical situations and analysts and has broad applicability beyond intelligence analysis.” Technology presents users with capabilities to build hierarchical argument templates that are ‘populated’ by the addition, weighting and fusion of evidence, all of which contribute to an overall judgment.

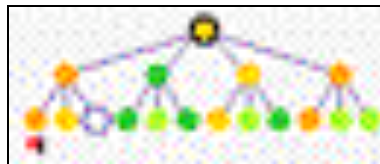


Figure 6. Generic representation of structured argumentation technology

Counterfactual #1: By studying Information Operations specialists, a closely related domain to and customer of intelligence analysis, Klein discovered that the natural reasoning style was more closely aligned with abductive, than deductive reasoning, due primarily to the high uncertainty within the events they were engaged in. “People are explanation machines.” IO specialists “were more likely to speculate about causes, given effects, than they were to deduce effects from causes. If one event preceded another (simple correlation), they speculated that the first event might have caused the second. They were actively searching for frames to connect the messages they were given....this is not deductive reasoning, but a form of reasoning that enables us to make sense of uncertain events. It is also a form of reasoning that permits us to generate new hypotheses, based on the frame we adopt.” The IO specialists also frequently demonstrated forms of “functional sensemaking,” which involves not just abstract reasoning but “developing an understanding of what can be accomplished and how capabilities can be expanded.”

Counterfactual #2: From observations in quasi-real-world experiments involving experienced intelligence analysts using real-world data against real-world problem sets, we have documented a number of barriers to sensemaking presented by structured argumentation, to include:

- Labor intensive, front-ended workload—i.e., high cognitive effort in building argument templates for specific problem sets;
- Confusion about, gaming of, or outright disregard for the fusion algorithms (which are intended to support the deductive reasoning);
- Lack of standards of judgment for answering and/or scoring questions within the arguments;
- Lack of clarity of the boundary conditions for the appropriateness of SA in analytic tasks;⁴

⁴ Johnston, R. (2005) has put this matter into more global terms, casting it even more bleakly: “I identified at least 160 [analytic methods for use in improving intelligence analysis]...[Yet] there is no body of research across the Intelligence Community asserting that method X is the most effective method for solving case one and that method Y is the most effective method for solving case two.”

- Partially successful attempts to marry SA to other intelligence analysis methodologies (e.g., Center of Gravity);
- Underspecified collaborative practices in constructing argument templates;
- Less than optimal support for collaborative argument building;
- Noticeable gaps in knowledge elicitation between expert knowledge and knowledge captured within arguments;
- Inappropriate requirements for low-level judgments within the ‘zone of indifference’—i.e., requiring analysts to make precise, numeric judgments that otherwise could ‘go either way’; and
- Discomfort with the inflexibility of argument structures, particularly the lack of capability to cross reference other parts of the argument.

Thus, in cases where “fundamental logical and analytic principles” are applied, their support for sensemaking appears questionable at best. At worst, they present an extremely time-consuming and confusing barrier to making sense of the world.

Assumption #2. Sensemaking builds up from data to produce a story.

- Commission: While in every case people are needed to see whether the proposed connections are real—and to be alert for intuitive but inchoate linkages—the Intelligence Community must more effectively employ technology to help draw attention to connections analysts might otherwise miss. (WMD, 2005)
- Concept: Evidence Extraction and Link Detection - developing techniques that allow [the identification of] relevant information—about links between people, organizations, places, and things—from the masses of available data, putting it together by connecting these bits of information into patterns that can be evaluated and analyzed, and learning what patterns discriminate between legitimate and suspicious behavior. (Senator, 2003).
- Technology: “Technology provides federal intelligence agencies the link analysis into social and organizational networks needed to ‘connect the dots’ - while improving organizational responsiveness and cross-departmental collaboration. Technology is the provider of advanced text-driven business intelligence solutions, providing the analytical bridge between unstructured text and enterprise data.” Technology provides a suite of capabilities to ingest documents, ontologically tag entities (e.g., people, places, things, events), create ‘links’ between the entities, and display the links in a variety of visualization schemes that provide drill down to the original documents.

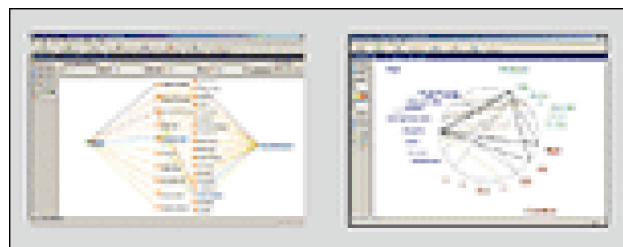


Figure 7. Generic representations of entity extraction and link detection technology

Counterfactual #1: The key to the Data/Frame Model of Sensemaking lies in the mutual interaction. As Klein notes: “We see sensemaking as the effort to balance these two entities—data and frames....Data are the interpreted signals of events; frames are the explanatory structures that account for the data. People react to data elements by trying to find or construct a story, script, a map, or some other type of structure to account for the data. At the same time, their repertoire of frames—explanatory structures—affects which data elements they consider and how they will interpret these data.” Frames, Klein notes, are usually not comprehensive models. Rather, people perform effectively using ‘fragmentary’ and ‘just-in-time’ mental models, both of which enable generalization across domains and building upon *local and dynamic* cause/effect connections they know about *in current contexts*.

Counterfactual #2: In frequent observations of entity extraction and link detection tools, we have documented these barriers to sensemaking, to include:

- Required document review to understand the actual nature of the automatically generated links;
- Lack of visibility to the algorithmic manipulation of the data;
- Contextually-nonspecific ‘tagging’ of entities;
- Conflation of the proximity of entities (e.g., closeness of terms within text) with ‘relationships’ and ‘links’; and
- Conflation of the number of links between entities with the ‘strength’ of relationships.

Thus, the Commission's recommendation of using people "in every case" to "be alert for intuitive but inchoate linkages," is no understatement. Without the human-provided frame, there is no sensemaking, and significant effort remains to comparing the data and frame.

Assumption #3. People should avoid premature consideration of a hypothesis

- Commission: The disciplined use of alternative hypotheses could have helped counter the natural cognitive tendency to force new information into existing paradigms. (WMD, 2005)
- Concept: Analysis of Competing Hypothesis (ACH) - ACH requires that you start with a full set of alternative possibilities (hypotheses) rather than a single most likely alternative. For each item of evidence, it requires you to evaluate whether this evidence is consistent or inconsistent with each hypothesis. Only the inconsistent evidence is counted when calculating a score for each hypothesis. The most probable hypothesis is the one with the least evidence against it, not the one with the most evidence for it. This is because ACH seeks to refute or eliminate hypotheses, whereas conventional intuitive analysis generally seeks to confirm a favored hypothesis (Pirolli et al., 2005a).
- Technology: Technology is an experimental program that provides a table oriented workspace for performing the ACH method. "Technology allows the analyst to sort and compare the evidence in various analytically useful ways. It sorts the evidence by diagnosticity, weight, type of source, and date/time. Evidence can be partitioned to compare the probabilities of the hypotheses based only on older evidence versus more recent evidence, or based on open sources versus clandestine sources, or based on the analyst's assumptions and logical deductions versus hard evidence."

Hypothesis	Evidence	Weight	Score	Consistency	Weight	Score	Consistency	Weight	Score
H1	E1	1	1	1	1	1	1	1	1
H1	E2	1	1	1	1	1	1	1	1
H1	E3	1	1	1	1	1	1	1	1
H1	E4	1	1	1	1	1	1	1	1
H1	E5	1	1	1	1	1	1	1	1
H1	E6	1	1	1	1	1	1	1	1
H1	E7	1	1	1	1	1	1	1	1
H1	E8	1	1	1	1	1	1	1	1
H1	E9	1	1	1	1	1	1	1	1
H1	E10	1	1	1	1	1	1	1	1
H1	E11	1	1	1	1	1	1	1	1
H1	E12	1	1	1	1	1	1	1	1
H1	E13	1	1	1	1	1	1	1	1
H1	E14	1	1	1	1	1	1	1	1
H1	E15	1	1	1	1	1	1	1	1
H1	E16	1	1	1	1	1	1	1	1
H1	E17	1	1	1	1	1	1	1	1
H1	E18	1	1	1	1	1	1	1	1
H1	E19	1	1	1	1	1	1	1	1
H1	E20	1	1	1	1	1	1	1	1
H1	E21	1	1	1	1	1	1	1	1
H1	E22	1	1	1	1	1	1	1	1
H1	E23	1	1	1	1	1	1	1	1
H1	E24	1	1	1	1	1	1	1	1
H1	E25	1	1	1	1	1	1	1	1
H1	E26	1	1	1	1	1	1	1	1
H1	E27	1	1	1	1	1	1	1	1
H1	E28	1	1	1	1	1	1	1	1
H1	E29	1	1	1	1	1	1	1	1
H1	E30	1	1	1	1	1	1	1	1
H1	E31	1	1	1	1	1	1	1	1
H1	E32	1	1	1	1	1	1	1	1
H1	E33	1	1	1	1	1	1	1	1
H1	E34	1	1	1	1	1	1	1	1
H1	E35	1	1	1	1	1	1	1	1
H1	E36	1	1	1	1	1	1	1	1
H1	E37	1	1	1	1	1	1	1	1
H1	E38	1	1	1	1	1	1	1	1
H1	E39	1	1	1	1	1	1	1	1
H1	E40	1	1	1	1	1	1	1	1
H1	E41	1	1	1	1	1	1	1	1
H1	E42	1	1	1	1	1	1	1	1
H1	E43	1	1	1	1	1	1	1	1
H1	E44	1	1	1	1	1	1	1	1
H1	E45	1	1	1	1	1	1	1	1
H1	E46	1	1	1	1	1	1	1	1
H1	E47	1	1	1	1	1	1	1	1
H1	E48	1	1	1	1	1	1	1	1
H1	E49	1	1	1	1	1	1	1	1
H1	E50	1	1	1	1	1	1	1	1
H1	E51	1	1	1	1	1	1	1	1
H1	E52	1	1	1	1	1	1	1	1
H1	E53	1	1	1	1	1	1	1	1
H1	E54	1	1	1	1	1	1	1	1
H1	E55	1	1	1	1	1	1	1	1
H1	E56	1	1	1	1	1	1	1	1
H1	E57	1	1	1	1	1	1	1	1
H1	E58	1	1	1	1	1	1	1	1
H1	E59	1	1	1	1	1	1	1	1
H1	E60	1	1	1	1	1	1	1	1
H1	E61	1	1	1	1	1	1	1	1
H1	E62	1	1	1	1	1	1	1	1
H1	E63	1	1	1	1	1	1	1	1
H1	E64	1	1	1	1	1	1	1	1
H1	E65	1	1	1	1	1	1	1	1
H1	E66	1	1	1	1	1	1	1	1
H1	E67	1	1	1	1	1	1	1	1
H1	E68	1	1	1	1	1	1	1	1
H1	E69	1	1	1	1	1	1	1	1
H1	E70	1	1	1	1	1	1	1	1
H1	E71	1	1	1	1	1	1	1	1
H1	E72	1	1	1	1	1	1	1	1
H1	E73	1	1	1	1	1	1	1	1
H1	E74	1	1	1	1	1	1	1	1
H1	E75	1	1	1	1	1	1	1	1
H1	E76	1	1	1	1	1	1	1	1
H1	E77	1	1	1	1	1	1	1	1
H1	E78	1	1	1	1	1	1	1	1
H1	E79	1	1	1	1	1	1	1	1
H1	E80	1	1	1	1	1	1	1	1
H1	E81	1	1	1	1	1	1	1	1
H1	E82	1	1	1	1	1	1	1	1
H1	E83	1	1	1	1	1	1	1	1
H1	E84	1	1	1	1	1	1	1	1
H1	E85	1	1	1	1	1	1	1	1
H1	E86	1	1	1	1	1	1	1	1
H1	E87	1	1	1	1	1	1	1	1
H1	E88	1	1	1	1	1	1	1	1
H1	E89	1	1	1	1	1	1	1	1
H1	E90	1	1	1	1	1	1	1	1
H1	E91	1	1	1	1	1	1	1	1
H1	E92	1	1	1	1	1	1	1	1
H1	E93	1	1	1	1	1	1	1	1
H1	E94	1	1	1	1	1	1	1	1
H1	E95	1	1	1	1	1	1	1	1
H1	E96	1	1	1	1	1	1	1	1
H1	E97	1	1	1	1	1	1	1	1
H1	E98	1	1	1	1	1	1	1	1
H1	E99	1	1	1	1	1	1	1	1
H1	E100	1	1	1	1	1	1	1	1

Figure 8. Generic representation of ACH technology

Counterfactual #1: Klein concludes with the data/frame concept "that a frame is needed to efficiently and effectively understand data, and that attempting to review data without introducing frames is unrealistic and unproductive." Similarly, Rudolph (cited in Klein (2004)) suggest that "failure to achieve early commitment to a frame can actually promote fixation because commitment to a frame is needed to generate expectancies (and to support the recognition of anomaly) and to conduct effective tests."⁵ This is not to say the first hypothesis will always be correct. When mental models include "bugs" of one sort or another, they can lead to the selection and/or misinterpretation of data. Feltovich, Coulson, and Spiro (2001) have catalogued a number of "knowledge shields" that people employ to explain away or account for anomalous data—the shields do not necessarily point toward truth or falsity, they simply provide mechanisms for handling data.

Counterfactual #2: Summarizing the findings of a simulation study in which 24 participants—half of whom had on average almost 10 years of intelligence analysis experience—used ACH to solve a typical, post facto analysis problem, Cheikes et.al. (2004) concluded that "Analysis of Competing Hypotheses [i.e., *the disciplined use of alternative hypotheses*] is intended to mitigate confirmation bias [i.e., *the natural cognitive tendency to force new information into existing paradigms*] in intelligence analysts. Unfortunately, there is no evidence that ACH reliably achieves this intended effect." Specifically, while there were indications that the participants gave more "weight" to confirming than to disconfirming evidence, "current beliefs did not influence the assessment of whether an evidence item was confirming or disconfirming. ACH did reduce confirmation bias, but the effect was limited to participants without professional analysis experience."

Thus, the jury remains out as to whether the use, disciplined or otherwise, of alternative hypothesis may help to counter any "natural" cognitive tendencies. The jury, however, in order to eliminate barriers against sensemaking, seemed poised to impose draconian measures against the use of ACH when they left the courtroom.

⁵ Hoffman (2005) has noted another stifling effect of ACH. The attempt to generate the universe of potential hypotheses can lead to a "combinatoric explosion" in which analysts must consider the nature and status each hypothesis before analysis of any of them might occur with respect to the current data.

Assumption #4. More data leads to better sensemaking

- Commission: "...analysts not only need more information, they also need new ways to manage what is already available to them." (WMD, 2005)
- Concept: automated message handling systems (amhs)⁶—An amhs receives message traffic from a variety of sources, stores it on disk, and then distributes it based on the address list and special handling indicators appearing in the message headers. It also compares received traffic against stored user and system profiles, and disseminates messages to analysts' message queues based on the results of these comparisons. It may send alarms for high precedence messages directly to the active user workstations.
- Technology: Technology was developed as an alert server for incoming message traffic. Messages are sorted via prebuilt schemas, or profiles, and disseminated accordingly into queues. The queues are represented visually by 3-D rendered "buildings," and alert notifications for messages are represented as a change in building color.

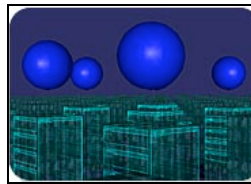


Figure 9. Generic representation of amhs technology

Counterfactual #1: In Klein's study of IO specialists, he noticed that novice specialists were sometimes hesitant to speculate without gathering additional data. Notably, none of the experts in the study were hesitant to speculate. Klein summarized the research on the value of more data by noting that while "accuracy increases with data elements up to a point (perhaps 8-10 data elements), [it] then asymptotes while confidence continues to increase" (Klein et al., 2004). Still other research has recently suggested that at some point increasing data may lead to worse decision quality." It also follows from the Data/Frame Model of Sensemaking that data is not simply managed during sensemaking—it is selected, defined, excluded, interpreted and evaluated for its pedigree. And performance of each of these tasks, in turn, requires a frame.

Counterfactual #2: Through cognitive task analysis interviews with users of amhs', we have collected these barriers to sensemaking:

- Lack of ownership or ability to develop and refine profiles;
- Lack of feedback on the efficacy of profiles;
- Nonexistence of standards for effective creation of profiles;
- Ad hoc 'scoring' and revision schemes;
- Little to no visibility of the data available;
- Sectioning of messages into different buildings;
- No visible effect on the reduction of 'circular reporting'; and
- Minimal support for review history in the context of team usage.

Thus, while the need for more data is at best questionable, the "new ways of managing" the data available to analysts impose greater, and probably less efficacious, demands than simply reviewing the data as it comes and actively searching for it—guided by the frame at hand.

CONCLUSION

Continuous transformation within the United States IC is necessary. Yet as we have shown, transformation with bases in something other than the actual cognitive work performed by the community's analysts might present barriers to effective sensemaking. We suggest empirically-based, piecemeal transformation as the best strategy to achieve successful transformation.

⁶ The use of lower case in the acronym "amhs" is appropriate enable explanation of the concept but avoid confusion with a similarly named system.

REFERENCES

- Cheikes, B., Brown, M. J., Lehner, P. E. and Alderman, L. (2004) MITRE Corporation, Bedford, MA.
- Cheikes, B. and Taylor, M. (2003) MITRE Corporation, Bedford, MA.
- Feltovich, P. J., Coulson, R. L. and Spiro, R. J. (2001) In *Smart machines in education* (Eds, Forbus, K. D. and Feltovich, P. J.) AAAI/MIT Press, Menlo Park, CA.
- Heuer, R. J., Jr. (1999) *Psychology of intelligence analysis*, Center for the Study of Intelligence, Central Intelligence Agency, Washington, D.C.
- Johnston, R. (2005) The Center for the Study of Intelligence, Washington, D.C.
- Kater, R. V., Montgomery, C. A. and Thompson, J. R. (1979) Army Research Institute, Army Project Number 2Q163743A774, Alexandria, VA.
- Klein Associates Inc. (2001). *Finding answers amidst uncertainty: Cognitive challenges of counter-terrorist analysts* (Semi-Annual Report sponsored by Defense Advanced Research Projects Agency issued by U.S. Army Aviation and Missile Command under Contract act # DAAH01-00-C-R094). Fairborn, OH: Klein Associates.
- Klein, G., Phillips, J. K., Rall, E. and Peluso, D. A. (2004) In *Expertise out of context: Proceedings of the 6th International Conference on Naturalistic Decision Making* (Ed, Hoffman, R. R.) Lawrence Erlbaum & Associates, Mahwah, NJ.
- Klein, G., Ross, K. G., Moon, B. M., Klein, D. E., Hoffman, R. R. and Hollnagel, E. (2003) *IEEE Intelligent Systems*, **18**, 81-85.
- Marrin, S. and Clemente, J. (2005) *International Journal of Intelligence and Counterintelligence*.
- McGroddy, J. C., and Herbert S. Lin, H. S. (Eds.) (2004). Committee on the FBI's Trilogy Information Technology Modernization Program, Computer Science and Telecommunications Board, Division on Engineering and Physical Sciences, The National Academies Press Washington, D.C.
- Mihelic, M. F. (2005) University of Tennessee, Knoxville, TN.
- Mills, G. H. (2003) Fairchild Paper, Air University Press.
- Myers, K. (2004) In *3rd International Conference on Systems Thinking in Management* University of Pennsylvania, Philadelphia, PA.
- Patterson, E. S., Watts-Perotti, J. C. and Woods, D. D. (1999) *Computer Supported Cooperative Work*, **8**, 353-371.
- Pirolli, P., Good, L., Heiser, J., Shrager, J. and Hutchins, S. (2005a).
- Pirolli, P. and Card, S. K. (2005b) In *International Conference on Intelligence Analysis* Tyson's Corner, VA.
- Senator, T. (2003) DARPA Tech 2002.
- Thompson, J. R., Hopf-Weichel and Geiselman, R. (1984) Army Research Institute, Research Report 1362, AD-A146, Alexandria, VA.
- WMD Commission. The Commission on the Intelligence Capabilities of the United States regarding Weapons of Mass Destruction (2005).