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Development and Content Validation of the Analysis Support Guide

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Abstract

Previous research has demonstrated that intelligence analysts do not routinely follow a logical ordinal workflow when performing analytic tasks; they do not always perform analytic activities along the workflow in an appropriate manner; and their training and experience are unrelated to their performance. In the present paper, we describe the development of the Analysis Support Guide (ASG) which aims to capture, communicate and encourage good analytic practice. Version V0.1 of the ASG was informed by intelligence organisational doctrine and past research on intelligence analysis. The ASG includes the generic analytic workflow, prompts for good practice at each stage of the workflow, indicators of good and poor analytic practice, and an analytic investigation questionnaire. Here, we report the findings of a small-scale content validation study of the ASG. Fourteen analysts were briefed on the ASG and they then provided detailed feedback on its content. The findings informed a revision of the ASG (i.e., V1.0). The ASG is now being used to train both new and experienced analysts. We discuss how the ASG can also be used to inform the development of analytic technologies, and future research on the psychology of intelligence analysis.

Keywords: Intelligence analysis, analytic workflow, analytic strategies, critical thinking

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Introduction

Despite the vast array of organizational policies on how intelligence analysis ought to be performed, as well as the testimonies of (retired) analysts and commentators describing how the analysis was conducted in a given context, there is a relative dearth of empirical research on how intelligence analysts perform analytical work.[1] The small body of existing research suggests that analysts may not work through workflows in an orderly manner, that analysts may not approach tasks along the workflow using critical thinking, and that analysts may be prone to bias.[2] Such practices can partly be explained by the complexities of the task, and the working environment of analysts can be quite challenging.[3] However, it is noteworthy that variables such as training and experience do not always differentiate between different levels of analytic performance.[4]

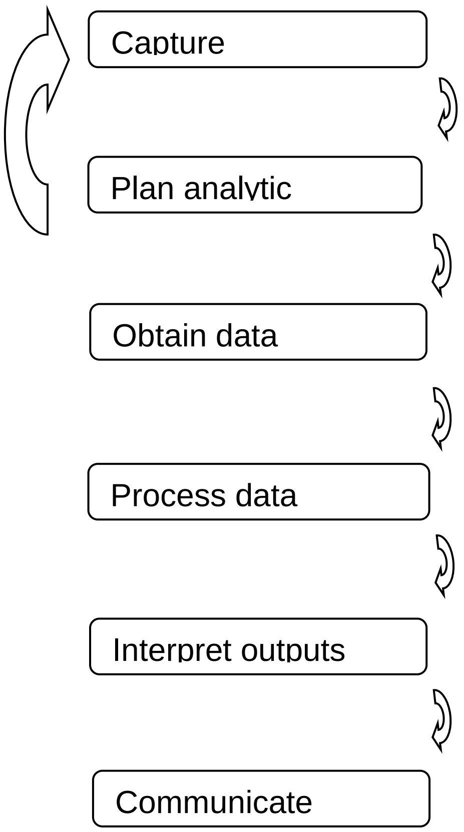
The intelligence community could, therefore, increase efforts to better communicate and encourage good analytic practice, both to new analysts as well as more experienced ones. However, traditional approaches to improving analysis through organizational doctrine and training on, for example, structured analytic techniques may be insufficient, partly because techniques are not evidence-based.[5] In other consequential domains such as the law, where judgments are typically based on partial and conflicting information, practitioners are often provided with guides to support their judgment process.[6] Such principles can promote both intuitive and critical thinking, as well as consistency, transparency, and accountability.[7]

This paper seeks to develop and validate a guide that provides analysts with a better understanding of analytic workflows and encourages analysts to adopt a critical and efficient approach to analysis. This guide can be used as a framework for analytic training, assessment of analytical performance, and development of new tradecraft, tools, and technologies. Before presenting the guide, a review the small body of past research provides a rationale for such a guide.

Generic analytic workflow

The generic analytic workflow was identified based on a review of the extant literature on analytic workflows, and the extent to which analysts followed the logical order of this workflow was examined.[8] The workflow is generic because it applies to various types of analysis (e.g., HUMINT, SIGINT, multi-source), conducted individually or in teams, and for various purposes (e.g., strategic, tactical). The workflow is separated into *six* different stages of activity that follow one another: capture requirements, plan an analytic response, obtain data, process data, interpret outputs, and communicate conclusions (see Figure 1).

Figure 1. **A model of the generic analytic workflow (also depicting an example of a 'loop back')**



The *capture requirements* stage is about understanding the customer's point of view, the wider context for the intelligence question, and what the ultimate aim or outcome is, as well as how the customer will achieve it. The *plan analytic response* stage is about identifying alternative methods that could be employed to fulfil the requirement, evaluating methods in terms of how effective and efficient they may be, and then making a prioritized plan for how to proceed. The *obtain data* stage is about extracting and selecting relevant data from the most appropriate sources in the most 'surgical' and efficient manner and establishing new sources of data if necessary. The *process data* stage is about manipulating the data using relevant analytic tools and techniques, including reformatting it and visualizing it. The *interpret outputs* stage is about testing alternative explanations for the output of the processing completed in the previous stage, constructing a logical argument to support the conclusion(s) drawn as well as taking account of alternative ones, and determining the level of confidence in these conclusions, as well as identifying any ambiguities. Finally, the *communicate conclusions* stage is about presenting the outcome of the analysis in a clear and meaningful format, distinguishing fact from inference, and expressing uncertainty and confidence.

Depending on the scale of the analytic problem and the analysts' experience, analysts might pass through some of the stages very quickly while remaining at other stages for some time. The workflow might be linear for simple, discrete analytic problems. However, the workflow might also be iterative for more complex analytic problems or a set of inter-connected problems making the task dynamic in nature (see feedback loop in Figure 1).[9]

Mandeep K. Dhami and Kathryn E. Careless argue that analysts should not skip or omit a stage of the workflow.[10] This is because a lack of ordinal structure may result in inconsistent working practices as well as for analytic work that lacks transparency, thus difficult to review or audit. In addition, divergence from an ordinal structure can lead to analytic products that do not fully satisfy the requirements, i.e., are ineffective. Finally, a lack of ordinal structure may lead to inefficient and resource-intensive (i.e., costly) working practices.

Dhami and Careless examined how 144 UK intelligence analysts ordered tasks along the generic analytic workflow.[11] Analysts were each presented with a list of six hypothetical activities that each represented one of the six stages of the generic analytical workflow. The analysts were asked to rank the activities in the order analysts would usually complete them in response to a brief analytical scenario. It was found that only 16% of analysts ranked all of the six activities presented in the logical order. Fourteen percent said they would only perform the activities in the first or second half of the workflow in the logical order. Thus, the majority of analysts applied less ordinal structure to analytic work. In particular, analysts were prone to 'skipping' or delaying the planning analytical response stage and prematurely interpreting outputs before processing the data. Furthermore, as Dhami and Careless note, analysts' training and experience were not associated with analysts' performance on the relatively straightforward workflow task analysts were asked to complete.

Some analysts might 'lose the thread' of the workflow, whereas others might start analytic work in a less orderly fashion but eventually 'grasp the thread' of the workflow. Some analysts may be keen to 'jump in' and collect and process data before planning their work, whereas others may rely on intuitive responses to the analytic problem rather than on critical thinking. Such working practices can lead to skewed or biased analytic outputs. The fact that analytic training and experience were not found to sufficiently encourage orderly working practices suggests that there is a potential need to introduce analytic support and guidance on the importance of following the generic analytic workflow.

Analytic strategies

Support and guidance should also emphasize the importance of applying critical thinking when performing analytic tasks.[12] Critical thinking requires analysts to apply the criteria of relevance, significance, accuracy, and credibility to the use of data.[13] It requires analysts to apply logic or reasoning to ascertain if certain conclusions follow from specific assumptions/propositions and think with consistency, depth, breadth, clarity, precision, and independence. Critical thinking can help analysts to clarify requirements, prioritize work, select relevant data, explore, compare and assess it, interpret the outputs of analysts' data processing, and communicate conclusions in a balanced way. An analyst who is not thinking critically may be more likely to apply an ineffective and/or inefficient strategy.

There is empirical evidence that this may be the case. For instance, in Emily Patterson et al.'s study, ten intelligence analysts described the strategies they used when performing a simulated analytic problem that involved using a database of 2000 mostly relevant text documents.[14] It was revealed that all analysts used primitive search strategies to narrow down the dataset; all opened from four to 29 documents only from a single search query, based on the documents' dates and titles. All analysts also relied heavily on one to four documents for analysis, read initial documents more carefully, and missed highly relevant data resulting in analysts making inaccurate statements. Some analysts missed critical events, forgot sources of text extracts, and missed data conflicts and updates.

George Chin et al. conducted an observational case study of five intelligence analysts working on two hypothetical analytic scenarios.[15] It was found that analysts did not always apply critical thinking. For example, analysts assumed the information was valid until proven otherwise, and the credibility of data was assessed subjectively. Similarly, in an observational study of four groups of ten military analysts completing an analytic task during a training exercise, Stoney Trent et al. found that analysts were likely to become fixated or anchored in a particular way of thinking about the problem.[16] Analysts also had difficulties in identifying relevant data in large datasets and had problems understanding analytic tools. Other researchers have demonstrated analysts' confirmation bias in selection and prioritization of data, and shown that analysts are prone to primacy effects.[17] Indeed, there is a growing body of research on cognitive biases and de-biasing in intelligence analysis.[18]

Dhami and Careless asked 113 UK intelligence analysts to rate how often they would apply various strategies to solving tasks along each stage of the analytic workflow.[19] The strategies presented at each stage were a priori designated as those involving deliberative or intuitive thinking. It was found that analysts reported using deliberative strategies significantly more often than intuitive ones when capturing customer requirements, processing data, and communicating conclusions. There was, however, 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. 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.

Richards J. Heuer and Randolph H. Pherson state, analysts might opt for a narrow and sometimes inappropriate range of approaches to analytic work because these might be those analysts learned during their formal education; those that are readily available to analysts; those that are driven by the data that is readily available (even if the data is not the right sort to help answer the question at hand); and those that are not time-consuming.[20] Beyond the resource costs of inefficient working and the risk of not fully completing analytic tasks within the required timeframes, the use of uncritical analytic strategies may lead to inaccurate and even biased conclusions. In addition, analysts may not adapt sufficiently to emerging analytic problems, i.e., those that require different/new working practices. This situation underscores the potential need to introduce analytic support and guidance on the importance of applying critical thinking to solving analytic tasks. The remainder of this paper describes the development and content validation of the Analyst Support Guide (ASG).

The Analyst Support Guide

Based on the above review of the extant literature, V0.1 of the ASG was developed. The ASG aims to support intelligence analysts in the application of good practices across the generic analytic workflow. It is intended for use by individual analysts working alone on analytic problems. Although the ASG has been developed for intelligence analysts working in one large organization, it is intended to be sufficiently generic so as to apply to other types of intelligence organizations.

Overall, the ASG presents analysts with the ‘generic analytic workflow,’ helps analysts to identify where along the workflow they might be at a given moment, provides prompts to encourage good practice, provides indicators of good and poor practice along the workflow, and contains a ‘pro forma’ for guiding and recording analysts’ work. The ASG comprises six sections. The first section provides a brief introduction to the function of the ASG and potential users.

The next section presents the six stages of the ‘generic analytic workflow.’ It provides a short description of what each stage entails and shows how the stages are linked. Thus, analysts are reminded that analytic work involves operational awareness, analytic strategy, smart data collection and retrieval, descriptive analysis, analytic reasoning, and ‘getting the point across.’

Another section helps analysts ‘find their way around the analytic workflow’ by providing a simple flowchart prompting tool to help analysts identify where along the analytic workflow they are at any given moment. This ensures that analysts do not skip or miss out on a stage by asking questions that must be answered before progressing to the next stage.

Another section provides a ‘good practice prompting tool,’ which describes the kinds of activities analysts are expected to perform at each stage of the workflow so as to encourage critical thinking (see Table 1). There are more or less effective and efficient ways of conducting the activities in Table 1. This is a prompt rather than a checklist. The activities that are likely to be relevant at each stage will depend on the analytic problem.

Table 1. Analyst activities along the workflow that encourage critical thinking

Stage	Activities expected at this stage
Capture requirements	• Identify customers • Understand customer perspectives • Understand customer's desired outcomes • Understand customer priorities
Plan analytic response	• Identify analytic line/hypothesis • Identify information required to disprove/corroborate analytic line • Identify alternative methods for obtaining information • Identify most effective and efficient method for obtaining information • Plan how you will record/structure the information
Obtain data	• Identify specific databases/sources • Construct queries • Retrieve outputs
Process data	• Understand what the data means (in plain English) • Identify unexpected or anomalous results and investigate them • Organise/structure the data in meaningful way
Interpret outputs	• Explain findings in multiple/alternative ways • Determine best explanation for data • Infer conclusions • Construct logical arguments to support conclusions • Assess your confidence in conclusions • Identify and explain remaining ambiguities

Communicate conclusions	• Record/communicate conclusions in an appropriate format • Distinguish between ‘facts’ and analytic conclusions • Express degree of confidence in the conclusions • Ensure output focuses on satisfying the customer’s requirement

Note. The present paper describes the development of the ASG and so the contents of this Table will have been updated after the validation study. See the Appendix for the revised version of the ASG.

A section presents ‘indicators of good practice along the analytic workflow’. These indicators are behaviors that would be expected to be performed at each stage of the workflow. Positive indicators are those conducted in accordance with good practice (see Table 2). Negative indicators are also presented to ensure analysts can clearly distinguish between good and poor practices (see Table 2). Table 2 is not intended to provide an exhaustive list of positive and negative indicators but simply examples of activities that are consistent and inconsistent with the best practice described here. This can be used as a checklist by analysts to assess their own performance. It can also be used to assess the performance of others.

Table 2. Indicators of good and poor practice along the analytic workflow

Stage	Indicators of good practice	Indicators of poor practice
Capture requirements	• Effort made to fully understand customer requirements better before jumping into action • Requirements are prioritised	• Going straight to data collection without any effort to further understand customer needs • Tries to do ‘everything’ rather than focus on directly enabling

	in-line with customer's needs	customer outcomes
Plan analytic response	• 'Taking a step back' from the problem to determine the best way to approach it before obtaining data • Hypotheses identified and plans to challenge hypotheses before seeking to corroborate/confirm them • Prioritised outcome- driven actions and next steps	• No evidence of thinking about how to approach the problem, next steps not prioritised • Either goes straight to 'favourite' data repositories, or does everything, focusing on activities rather than outcomes • No hypotheses identified where appropriate • Plans to corroborate/confirm hypotheses before challenging them
Obtain data	• 'Surgical' approach to obtaining data, only looking in relevant places for specific things • Data collection is focussed on the key question • All relevant strands/sources are utilised	• Looking everywhere, or in favourite sources without any indication of prioritisation, economical use of resources • Data collection includes irrelevant information or too much redundant information • Whole or partial relevant strands of intelligence/activity or data sources are excluded
Process data	• Content/data accurately	• Content/data inaccurately

	described • Draws disparate sources of information together while pulling apart different strands of activity • Understands technical aspects of data and seeks help from relevant experts if necessary • Proactively seeks anomalous data – looks for the 'black swans'	described and/or mixes different strands of activity • Misunderstanding of technical aspects of data • Ignores data that is difficult to understand or doesn't fit with own assumptions • No effort made to investigate and understand unexpected data points
Interpret outputs	• More emphasis given to data that disproves/contradicts hypotheses and discriminates between hypotheses over data that corroborates • Makes analytic judgements • Constructs sound arguments to support conclusions	• More emphasis given to corroborative information, ignores or overlooks data that disproves hypotheses • Lack of analytic judgements made • Lack of reasoning to support conclusions
Communicate conclusions	• Clear and concise communication style – easy to follow • Provides rationale underlying conclusions	• Unclear and verbose communication style • Refusal/reluctance to communicate conclusions until more information received and/or ambiguities have

	drawn • Distinguishes between degree of uncertainty around conclusions and level of confidence in conclusions • Fully explains ambiguities • Distinction made between ‘fact’ and analysis • Analytic conclusions are directly related to customer’s needs	all been resolved • Ambiguities left unexplained or excluded • Lacks distinction between ‘fact’ and analysis • Analytic conclusions are not directly related to answering the customer’s needs

Note. The present paper describes the development of the ASG and so the contents of this Table will have been updated after the validation study. See the Appendix for the revised version of the ASG.

The final section of the ASG provides analysts with an ‘analytic investigation pro forma.’ This is designed to guide analysts through an analytic problem and so lists a set of questions asking analysts to think about the outcomes of the activities that they might be expected to perform at each stage of the analytic workflow. For instance, at the processing data stage, analysts are asked: ‘Was there anything unexpected or anomalous?’ The pro forma can be used by analysts to record their work and is formatted as a removable workbook. Documenting their own work at each stage should help analysts organize and focus analysts’ work, as well as allow transparency and accountability.

Content validation of the Analysis Support Guide

A content validation study was conducted on V0.1 of the ASG in order to assess if its content represented all facets of what could be described as good analytic practice in terms of orderly workflows and critical thinking.

Fourteen analysts from one intelligence organization volunteered to participate in the validation study. The analysts were either currently engaged in analytic work or had been in the past (and now working in management and training of analysts). The analysts had all worked in a variety of operational teams and had a range of analytic experience.

The data was collected in small groups. Respondents were first were briefed on the aims and contents of V0.1 of the ASG and were then asked to individually provide detailed feedback on its content. Specifically, respondents were asked to comment on the representativeness of the ‘generic analytic workflow,’ the appropriateness of the examples of good and poor analytic practice, and the helpfulness of the ‘pro forma’ that prompts good practice. Respondents were also asked whether any information should be included or excluded. Responses were elicited using a combination of closed- and open-ended questions. Responses to the closed-ended questions were all measured on 11-points scales anchored at each end from ‘not at all’ (i.e., 1) to ‘completely’ (i.e., 11), and the group means and standard deviations are reported here. A ‘not sure’ response option was also available for all questions. However, none of the respondents used this option. A copy of the validation survey is available from the first author.

The ‘Generic Analytic Workflow’

On average, respondents generally believed that the section on the ‘generic analytic workflow’ represents a model of ‘high-level technology agnostic’ workflow that should be used by typical analysts within the organization (M = 8.57, SD = 1.60). None of the respondents said that any of the six stages of the workflow should be excluded. Similarly, none said that any of the main stages of the analytic workflow were missing.

Six respondents commented on the description of the ‘generic analytic workflow.’ Of particular use was the suggestion that greater emphasis is placed on the flexibility of the workflow, where analysts could ‘loop back’ to previous stages, and where analysts might spend more or less time at each stage depending on, for example, analysts’ experience with the task.

‘Finding Your Way around the Analytic Workflow’

The quantitative data suggested that, to some extent, respondents thought the flowchart would help analysts identify which stage they are in (M = 7.14, SD = 1.66). However, the qualitative comments from nine of the respondents indicated that there was room for improvement. In particular, there was a belief that the flowchart was too simplistic and might be patronizing. It was suggested that it might be helpful to incorporate the good practice prompts within the flowchart. However, this would be difficult in an initial paper version of the ASG, although it would be possible with a future version embedded within an analytic tool. Thus, the conclusion was to delete this section of the ASG.

‘Good Practice Prompting Tool’

Respondents agreed that the activities listed for the six stages along the analytic workflow represented good practice (see the second column of Table 3). In addition, 13 respondents commented on understanding the requirements, plan an analytic response, and the obtain data stages of the ‘good practice prompting tool.’ In particular, for the understand requirements stage, respondents suggested making the language less (other) customer-focused since an analyst might be investigating a problem where they are essentially their own customer (e.g., when an analytic problem is broken down into a constituent part of a larger problem). Respondents also suggested emphasizing the need to challenge the customer, if necessary.

Table 3. Means and standard deviations of responses to some items in the validation survey

	Good practice prompting tool	Positive indicators of good practice	Negative indicators of good practice	Analytic investigation pro forma
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Capture requirements	9.50 (1.45)	9.21 (1.53)	8.29 (1.82)	8.86 (1.96)
Plan analytic response	8.21 (1.89)	8.50 (1.29)	7.79 (1.93)	9.07 (1.69)
Obtain data	8.79 (1.48)	8.50 (1.65)	7.93 (1.94)	8.08 (2.14)
Process data	9.29 (1.20)	9.36 (1.60)	9.38 (1.39)	9.15 (1.14)
Interpret data	9.50 (1.29)	9.57 (1.09)	9.64 (.93)	9.77 (.93)
Communicate conclusions	9.43 (1.16)	10.14 (.86)	9.57 (1.65)	9.92 .95)

Note. Responses were measured on 11-point scales (from 1 to 11). Higher scores reflect greater agreement with the contents of V0.1 of the ASG.

For the plan analytic response stage, respondents suggested emphasizing the need to identify the timeline for the task as well as the available resources that could be used and recognizing any constraints. Finally, for the obtain data stage, respondents suggested that the identification of data sources ought to be moved to the plan analytic response stage and that there was a need to emphasize the importance of consulting with others when obtaining data.

Indicators of Good Practice along with the Analytic Workflow

Respondents agreed that the ‘positive indicators’ listed for each stage of the analytic workflow are examples of efficient and/or effective practice (see the third column of Table 3). Nine respondents commented on the ‘positive indicators’ associated with the plan analytic response and obtain data stages. In particular, for the plan analytic response stage, respondents suggested making it clearer what “prioritized outcome-focused driven actions & next steps” means and adding an indicator that demonstrates the analyst considered the constraints. For the obtain data stage, it was also suggested that an indicator for considering the constraints should be added.

Respondents generally agreed that the ‘negative indicators’ listed for each stage of the analytic workflow are examples of inefficient and/or ineffective practice (see the fourth column of Table 3). Twelve respondents commented on the ‘negative indicators’ associated with the understanding of requirements, plan analytic responses, and obtain data stages. Of particular use were the suggestions to make clearer what “plans to seek corroboration/confirmation before challenging” means and to soften the tone when referring to the negative aspect of analysts going directly to their “favorite data repositories” in the plan analytic response stage.

‘Analytic Investigation Pro Forma’

Finally, respondents agreed that the questions in the pro forma pertaining to each stage of the analytic workflow would help analysts to perform activities that represent good practice (see the final column of Table 3). Nine respondents commented on understanding the requirements and obtain data stages of the ‘analytic investigation pro forma.’ Of particular use were the suggestions to move consideration of the resources and time available from the understanding requirements to the plan analytic response stage and not to limit the number of priorities an analyst might have. For the obtain data stage, it was suggested not to use the word 'query' as it was too exclusive to the many ways in which data may be obtained. In structured discussions with respondents after completion of the survey, many felt that the pro-forma was 'off-putting' and lengthy. It was suggested that although the content was useful, it might be more useful if incorporated into existing tools rather than as a separate workbook which gave the impression of being 'another thing to fill in.' It was therefore decided to remove this section from the ASG and replace it with a simplified one-page section containing all of the prompting questions without the form-formatted boxes to fill in. There are plans to seek other ways to incorporate this content into the analysts' environment.

Discussion

Ideally, the quality of intelligence analysis ought to be assessed based on the accuracy of the conclusions drawn. However, obtaining timely, reliable, and valid outcome feedback is inherently difficult for many types of intelligence problems (for a notable exception, see David R. Mandel and Alan Barnes).[21] Therefore, the quality of intelligence analysis has been typically based on the integrity of the process taken to draw the conclusions, as this can be more easily assessed. A review of best practices in the intelligence community and academic research into effective analytical workflows concluded that two of the basic criteria for a good process are that it is *ordered* and involves *critical thinking*. It is assumed that a good process can lead to a good outcome.[22]

Psychologists have pointed out that people generally avoid critical thinking and so substitute a difficult cognitive task with an easier one that people try to solve using intuitive or heuristic strategies.[23] Such practices can partly be explained by the complexities of the task and the limitations of the unaided mind.[24] Indeed, past research reviewed above has revealed that intelligence analysts do not routinely follow a logical ordinal workflow when performing analytic tasks; that analysts do not always perform analytic activities along the workflow using critical thinking, and that analysts' training and experience are largely unrelated to analysts' performance. This situation necessitates the development and implementation of some form of analytic 'guide' that both prescribes and supports good analytic practice along the full spectrum of the analytic workflow.

This paper has described the evolution of such a guide, i.e., V1.0 of the Analyst Support Guide (ASG; see Appendix). The ASG was informed by intelligence organizational doctrine and research on intelligence analysis, as well as findings from the small-scale validation study presented in this report. The ASG presents the 'generic analytic workflow,' provides indicators of good and poor practice along the workflow, and provides prompts encouraging good practice. Thus, the ASG encourages analysts to work in an ordered fashion and with a critical mindset.

The validation study presented here revealed that relatively minor revisions needed to be made to the original version of the ASG (V0.1), and these were made as follows:

- The Introduction to the section entitled 'The Generic Analytic Workflow' was updated as suggested.
- The section entitled 'Finding Your Way around the Analytic Workflow' was deleted.
- Revisions were made as suggested to the description of the understand requirements, plan an analytic response and obtain data stages in the section entitled 'Good Practice Prompting Tool.'
- Revisions were made as suggested to the positive and negative indicators for the understanding requirements, plan an analytic response and obtain data stages in the section entitled 'Indicators of Good Practice along with the Analytic Workflow.'
- Revisions were made as suggested to the questions listed in the section entitled 'Analytic Investigation Pro Forma,' and the self-completion forms were deleted and replaced with a simplified question-based prompt page.

Thus, the findings of the validation study informed the development of V1.0 of the ASG, which is presented in the Appendix. This now comprises five sections. Section A provides a brief introduction to the ASG. Section B presents the 'generic analytic workflow.' Section C provides a 'good practice prompting tool.' Section D provides 'indicators of good practice along the analytic workflow' (along with indicators of poor practice). Finally, Section E provides an 'analytic investigation questionnaire' that helps analysts apply good practice.

The ASG differs from other efforts to improve analysis, such as where researchers have explored prescriptive strategies for analysis in the context of developing technological tools to support analysis. For example, Joshua Phillips et al. designed an intelligent system to support analysts using case-based reasoning, where the system assesses a new situation by comparing its features with existing cases.[25] Nicholas J. Pioch and John O. Everett designed software called POLESTAR (POLicy Explanation using STories and ARguments) to support analysts' work by allowing analysts to spatially organize and cluster information, create timelines, construct arguments, and obtain peer review.[26] However, such efforts at technologically supporting analysts do not always cover the types of analytic tasks that analysts must perform along the whole analytic workflow (i.e., from capture requirements to communicate conclusions). Such studies are also typically focused on obtaining and processing data. By contrast, the ASG aims to support analysis along the full spectrum of tasks performed across the whole analytic workflow. In order to realize the benefits of the ASG, prompts or 'nudges' ought to be seamlessly incorporated into the analyst's natural environment by embedding elements of it into the technologies that analysts use for different stages of the workflow.

Future directions and implications

The next step is to empirically test the effectiveness of the ASG by examining the extent to which it improves analytic performance measured on a range of criteria (e.g., validity and reliability of conclusions drawn). Ideally, this ought to be done using a randomized control trial, involving a sufficiently large sample of more and less experienced analysts performing representative analytic tasks. The authors are currently undertaking such an endeavor.

The ASG can be further developed by including suitable guidance on the sorts of analytic techniques (e.g., cognitive strategies) that ought to be applied at each stage of the analytic workflow. For instance, Dhami et al.[27] identified 75 structured analytic techniques that were potentially applicable to analytic tasks. Techniques were categorized as having at least one of 12 primary functions and so could be arranged across the analytic workflow according to the techniques' primary function. The primary functions were: generating scenarios (including ideas/questions/hypotheses/options), clarification, determining the usefulness of data, critiquing, reducing disagreement or reaching consensus, identifying/monitoring patterns (trends) over time, identifying/understanding (non-causal) relations, identifying/understanding cause-effect relations, hypothesis testing, forecasting/prediction, deciding/choosing, constructing a message, and presenting a message.

In addition, the ASG can be extended to include relevant de-biasing strategies so that analysts do not fall prey to cognitive biases at particular stages of the workflow. Ian K. Belton and Mandeep K. Dhami recently identified eight biases that may manifest at various stages of the analytic workflow (i.e., belief bias, confirmation bias, explanation bias, fluency effects, framing effects, order effects, the planning fallacy, and overconfidence).[28] The researchers also identified relevant psychologically informed and empirically tested de-biasing interventions. For example, several variations of the 'consider-the-opposite' strategy have been found to reduce confirmation bias.

It is anticipated that the ASG can be used to train new analysts and improve and assess the performance of experienced analysts. For instance, are analysts following the ordinal structure of the workflow? And, are analysts using recommended practices at each stage of the workflow? The ASG is currently being used to train new analysts at one large UK intelligence agency. Over 200 analysts had received a five-day introductory course built around the workflow. Analysts are assessed on application of the workflow at regular intervals throughout the course and provided feedback on the areas where analysts demonstrated good practice and areas where analysts should continue to improve upon. Initial feedback from analysts regarding the course has been positive, with analysts recognizing the importance of the six stages of the workflow and in applying the principles of good practice in analytic work.

The ASG can also be used to inform the further development of tools that analysts currently use so as to enhance the ordinal structure of analytic workflows and the application of critical thinking at each stage of the workflow. Indeed, the ASG provides an enduring framework for intelligence analysis that can be used as a scaffold for building new analytic tradecraft and technology.

Finally, by unpacking the 'black box' of intelligence analysis, the ASG itself can direct future research on the psychology of intelligence analysis. For instance, researchers can focus research on specific stages of the workflow, and examine how long analysts spend at each stage, when and why analysts move to the next stage, as well as when and why analysts return to previously visited stages. Researchers can also investigate the conditions that may affect analysts' ability to apply good practice at specific stages of the workflow, such as task complexity and experience. A deeper understanding of how analysts think and work could potentially be used to both improve analysts' working conditions and training.

References

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[1] UK MoD, "Quick wins for busy analysts", *Published by Defence Intelligence*, UK, 2013. US Government, "A tradecraft primer: Structured analytic techniques for improving intelligence analysis", 2009; Bar-Joseph, U., & Kruglanski, A. W., "Intelligence failure and the need for closure: On the psychology of the Yom Kippur surprise", *Political Psychology,* Vol. 24, 2003, pp.75-99. Betts, R. K., "Two faces of intelligence failure: September 11 and Iraq's missing WMD", *Political Science Quarterly,* Vol. 122, 2007, pp.585-606. Goodwin, J., "Why we were surprised (again) by the Arab spring", *Swiss Political Science Review,* Vol.17, 2011, pp.452-456.

[2] Dhami, M. K. & Careless, K. "A survey of intelligence analysts' strategies for solving analytic tasks", Military Psychology, Vol.31, 2019, pp. 117-127. Dhami, M. K., & Careless, K. E, "Ordinal structure of the generic analytic Workflow: a survey of intelligence analysts", 2015 European Intelligence and Security Informatics Conference, 2015b, pp.141-144. Cook, M. B., & Smallman, H. S, "Human factors of the confirmation bias in intelligence analysis: Decision support from graphical evidence landscapes", *Human Factors: The Journal of the Human Factors and Ergonomics Society,* Vol.50, 2008, pp.745-754. Patterson, E. S., Roth, E. M., & Woods, D. D., "Predicting vulnerabilities in computer-supported inferential analysis under data overload", *Cognition, Technology & Work,* Vol.3, 2001, pp.224-237.

[3] Chin, G. Jr., Kuchar, O. A., & Wolf K. E, "Exploring the analytical processes of intelligence analysts", IEEE International Conference on Systems, Man and Cybernetics, 2009, pp.11-20. Dhami, M. K., & Careless, K. E, "Intelligence analysis: Does collaborative analysis outperform the individual analyst?", The Journal of Intelligence Analysis, 2015a, pp.22. Hutchins, S. G., Pirolli, P., & Card, S., "Use of critical analysis method to conduct a cognitive task analysis of intelligence analysts", Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol.47, 2003, pp.478-482. Trent, S., Voshell, M., & Patterson, E., "Team cognition in intelligence analysis", Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol.51, 2007, pp.308-312.

[4] Dhami, M. K. & Careless, K. "A survey of intelligence analysts' strategies for solving analytic tasks.".

[5] Dhami, M. K., Mandel, D. R., & Belton, I., "The 'Analysis of Competing Hypotheses' in intelligence analysis" Applied Cognitive Psychology, Vol.31, 2019, pp. 1080-1090. Mandel, D. R., Karvetski, C. W., & Dhami, M. K. "Boosting intelligence analysts' judgment accuracy: What works, what fails?" Judgment and Decision Making, Vol.13, 2018, pp. 607-621. Dhami, M. K., Mandel, D. R., Mellers, B., & Tetlock, P, "Improving intelligence analysis with decision science", Perspectives on Psychological Science, Vol.10, 2015, pp.753-757.

[6] Dhami, M. K, "A 'decision science' perspective on the old and new sentencing guidelines in England and Wales" In A. Ashworth & J. V. Roberts (Eds.), Structured sentencing in England and Wales: From guidance to guidelines, 2013a, pp.165-181, Oxford: Oxford University Press. Dhami, M. K, "Sentencing guidelines in England and Wales: Missed opportunities?", Law and Contemporary Problems, Vol.76, 2013b, pp.287-305.

[7] Dhami, M. K., Belton, I., & Goodman-Delahunty, J, "Quasi-rational models sentencing", *Journal of Applied Research on Memory and Cognition,*Vol.4, 2015, pp.239-247.

[8] Bier, E. A., Card, S. K., & Bodnar., "Entity-based collaboration tools for intelligence analysis", In D. Ebert, & T. Ertl (Eds.), IEEE Symposium on Visual Analytics Science and Technology (VAST), 2008, (pp. 99-106). Elm, W., Potter, S., Tittle, J., Woods, D., Grossman, J., & Patterson, E., "Finding decision support requirements for effective intelligence analysis tools", Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol.49, 2005, pp.297-301. Farry, M., Carlson, E., & Mahoney, S., "The mutual support function model: A cognitive model for intelligence analysis supporting irregular warfare", Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol.55, 2011, pp.880-884. Kang, Y. & Stasko, J., "Characterizing the intelligence analysis process: Informing visual analytics design through a longitudinal field study", In G. Santucci & M. Ward (Eds.), IEEE Conference on Visual Analytics Science and Technology (VAST), 2011, pp.21-30. Klein, G., Moon, B., & Hoffman, R. R., "Making sense of sensemaking 2: A macrocognitive model", IEEE, Intelligent Systems,Vol.21, 2006, pp.88-92. Moore, D. T., "Sensemaking: A structure for an intelligence revolution", 2011, Available at http://www.nil-u.edu/ni_press/pdf/Sensemaking.pdf Phillips, J., Liebowitz, J., & Kisiel, K., "Modeling the intelligence analysis process for intelligent user agent development", Research and Practice in Human Resource Management, Vol.9, 2001, pp.59-73. Pirolli, P., & Card, S. K., "The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis", Proceedings of International Conference on Intelligence Analysis, Vol.5, 2005, pp.2-4. Available at http://vadl.cc.gatech.edu/documents/2_card-sensemaking.pdf Roth, E. M., Pfautz, J. D., Mahoney, S. M., Powell, G. M., Carlson, E. C., Guarino, S. L., Fichtl, T. C., & Potter, S. S. (2010). Framing and contextualizing information requests: Problem formation as part of the intelligence analysis process. Journal of Cognitive Engineering and Decision Making, 4, 210-239.

[9] Brehmer, B., "Dynamic decision making: Human control of complex systems", Acta Psychologica, Vol.81, 1992, pp.211-241.

[10] Dhami, M. K., & Careless, K. E, "Ordinal structure of the generic analytic Workflow: a survey of intelligence analysts."

[11] Dhami, M. K., & Careless, K. E, "Ordinal structure of the generic analytic Workflow: a survey of intelligence analysts."

[12] Harris, D. H., & Spiker, V. A., "Critical thinking skills for intelligence analysis", In E. L. Nunes (Ed.), Ergonomics: A systems approach, 2010, pp.209-232, Available at www.intechopen.com/books/ergonomics-a-systems-approach/critical-thinking-skills-for-intellgienceanalysis Moore, D. T., "Critical thinking and intelligence analysis", Washington, DC: NDIC Press, 2007.

[13] Harris, D. H., & Spiker, V. A., "Critical thinking skills for intelligence analysis", pp.209-232. Hughes, W., & Lavery, J., *Critical thinking: An introduction to the basic skills*, 4th edition, Ontario: Broadview Press Ltd, 2004.

[14] Patterson, E. S., Roth, E. M., & Woods, D. D., "Predicting vulnerabilities in computer-supported inferential analysis under data overload." See also Dominguez, C., Cox, D., Long, W. G., Moon, G., & Klein, G, "Helping analysts deal with data overload: Profiling profilers", Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol.49, 2005, pp.908-912.

[15] Chin, G. Jr., Kuchar, O. A., & Wolf K. E, "Exploring the analytical processes of intelligence analysts."

[16] Trent, S., Voshell, M., & Patterson, E., "Team cognition in intelligence analysis."

[17] Cook, M. B., & Smallman, H. S, "Human factors of the confirmation bias in intelligence analysis: Decision support from graphical evidence landscapes."Wickens, C., Ketels, S. L., Healy, A. F., Buck-Gengler, C. J., & Bourne, L. E., Jr., "The anchoring heuristic in intelligence integration: A bias in need of de-biasing", Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol.54, 2010, pp.2324-2328.

[18] Billman, D., Convertino, G., Shrager, J., Pirolli, P., & Massar, J., “Collaborative intelligence analysis with CACHE and its effects on information gathering and cognitive bias”, Paper presented at the Human Computer Interaction Consortium Workshop. Available at http://www2.parc.com/istl/groups/uir/publications/items/UIR-2006-09- Dunbar, N. E., Miller, C. H., Adame, B. J., Elizondo, J., Wilson, S. N., Lane, B. L., Kauffman, A. A., Bessarabova, E., Jensen, M. L., Straub, S. K., Lee, Y, Burgoon, J. K., Valacich, J. J., Jenkins, J., & Zhang, J., “Implicit and explicit training in the mitigation of cognitive bias through the use of a serious game” Computers in Human Behavior, 2014, Vol.37, pp.307-318. Morewedge, C. K., Yoon, H., Scopelliti, I., Symborski, C. W., Korris, J. H., & Kassam, K. S., “Debiasing decisions: Improved decision making with a single training intervention”, Policy Insights from the Behavioral and Brain Sciences, Vol.2, 2015, pp.129-140. Symborski, C., Barton, M., Quinn, M., Morewedge, C. K., Kassam, K. S., & Korris, J. H., “Missing: A serious game for the mitigation of cognitive biases”, Proceedings of the Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC), 2014, Available at http://www.iitsec.org/about/PublicationsProceedings/Documents/BP_TRNG_14295_Paper.pdf See also Belton, I. K., & Dhami, M. K., “Cognitive biases and debiasing relevant to intelligence analysis”, In R. Viale (Ed.), Handbook on Bounded Rationality, 2021. London: Routledge.

[19] Dhami, M. K. & Careless, K. “A survey of intelligence analysts’ strategies for solving analytic tasks.”

[20] Heuer, R. J., & Pherson, R. H., “Structured analytic techniques for intelligence analysis”, Washington DC: CQ Press, 2008.

[21] Mandel, D. R., & Barnes, A., “Accuracy of forecasting in strategic intelligence”, Proceedings of the National Academy of Sciences, Vol.111, 2014, pp.10984-10989.

[22] Edwards, W, “What constitutes ‘a good decision’?”, Acta Psychologica, Vol.56, 1984, pp.5-27.

[23] Kahneman, D., “Thinking, fast and slow”, New York: Farrar, Straus and Giroux, 2011.

[24] Gigerenzer, G., Todd, P. M., & the ABC Research Group, “Simple heuristics that make us smart”, Oxford: Oxford University Press, 1999. Hammond, K. R., “Human judgment and social policy: Irreducible uncertainty, inevitable error, and unavoidable injustice”, Oxford, England: Oxford University Press, 1996. Hammond, K. R., “Judgments under stress”, Oxford, England: Oxford University Press, 2000.

[25] Phillips, J., Liebowitz, J., & Kisiel, K., “Modeling the intelligence analysis process for intelligent user agent development.”

[26] Pioch, N. J. & Everett, J. O., “POLESTAR: Collaborative knowledge management and sensemaking tools for intelligence analysts”, In Proceedings of the 15th ACM International Conference on Information and Knowledge Management, CIKM 2006, pp. 513-521.

[27] Dhami, M. K., Belton, I., & Careless, K., “Critical review of analytic techniques” 2016 European Intelligence and Security Informatics Conference, 2016, pp. 152-155.

[28] Belton,, I. K., & Dhami, M. K., “Cognitive biases and debiasing relevant to intelligence analysis.”

Appendix

CONTENTS

A. INTRODUCTION

Version 1 of this Guide aims to support intelligence analysts in the application of good practices across the generic analytic workflow. It is intended for use by individual analysts working alone on analytic problems. It is intended to be a reference aid to a way of working not a 'how to' or prescriptive guide to being an Intelligence Analyst.

The Guide combines relevant concepts from scientific research in cognitive psychology and decision science and existing intelligence organisational doctrine, as well as recent novel research within the organisation.

Although the Guide has been developed for intelligence analysts working in a SIGINT organisation, it is intended to be sufficiently generic so as to apply to other types of analysis.

Subsequent versions will aim to offer recommended structured analytic techniques for use at each stage. The long-term ambitions are for the contents of this guide to be incorporated into the day-to-day workflow of Analysts fully embedded into the tools, environment, training, development and support of Intelligence Analysts.

B. THE GENERIC ANALYTIC WORKFLOW

This diagram details the 6 stages of the generic Analytic Workflow and gives a short description of what each stage entails.

1. Understand requirements - *Operational awareness*

This stage is about understanding the customer's point of view, the wider context for the immediate requirement or intelligence question, and what the ultimate aim or outcome is (e.g. disruption) and how it will be achieved.

2. Plan analytic response - *analytic strategy*

This stage is about identifying alternative methods that could be employed to fulfil the requirement, evaluating them in terms of how efficient & effective they may be and then making a prioritised plan for how to proceed.

3. Obtain data - *smart data collection & retrieval*

This stage is about extracting, filtering & selecting the relevant data from the most appropriate sources. It will involve being able to query multiple data sources in the most surgical and efficient way or establishing new sources of data if nothing currently exists.

4. Process data - *descriptive analysis*

This stage is about understanding the raw data output of a tool, and being able to describe accurately (in plain English) what the data means. It may involve exporting data from multiple sources & reformatting into composite charts, diagrams or other visualisations.

5. Interpret data - *analytic reasoning*

This stage is about testing alternative explanations for the (often incomplete) 'facts', and constructing strong logical arguments to support conclusions as well as dismiss alternative hypotheses. It may involve distinguishing between different strands of activity.

6. Communicate conclusions - *getting the point across*

This stage is about presenting & communicating the outcome of analysis in a clear, meaningful, and relevant way. It will involve determining the appropriate medium to share conclusions, as well as highlighting & explaining areas of uncertainty

Notes for use

Looping back / iterating: It is conceivable that Analysts may need to loop back to previous stages and iterate especially when working on complex problems. It is recommended that complex problems are broken down during the planning stage to an appropriate scale. Having identified an appropriately scaled requirement the Analyst might then loop back to the requirements phase before planning how to answer that specific problem. The key when iterating is to **not skip stages**. The 6 stages of the workflow should always be done in this order without omitting stages. It is expected that experienced Analysts will progress through some stages relatively quickly making some stages almost unconscious. Experts going through stages relying on unconscious intuition is perfectly valid as long as the thought process is made explicit allowing it to be challenged, recorded and explained.

C. GOOD PRACTICE PROMPTING TOOL

This chart describes the kind of activities you should expect to perform at each stage. It should be used as a prompt not a checklist. It is likely that not all the activities included here will be relevant at each stage - the ones that are relevant will depend on the specific requirement.

1. Understand requirements

- Identify customers (this could be yourself)
- Understand customer perspectives & drivers
- Understand customer outcomes – what are they ultimately trying to achieve?
- Understand customer priorities – challenge if required

2. Plan analytic response

- Identify the analytic line / hypothesis
- Identify information requires to disprove / corroborate
- Identify alternative methods for obtaining this data
- Identify most effective & efficient method
- Plan how you will record / structure your data

3. Obtain data

- Access specific database / source (or identify someone else to access for you)
- Construct query
- Retrieve output

4. Process data

- Record nil return (no data)
- Understand what the data means (in plain-English)
- Identify unexpected or anomalous results & investigate
- Organise / structure data in a meaningful way

5. Interpret data

- Explain findings in multiple ways
- Determine which is the best explanation
- Infer conclusions
- Construct logical arguments
- Assess confidence in your conclusions
- Identify remaining ambiguities

6. Communicate conclusions

- Record / communicate conclusions in appropriate format
- Distinguish between ‘facts’ and analytic conclusions
- Express degree of confidence in conclusions
- Ensure output focuses on satisfying the requirement

D. INDICATORS OF GOOD PRACTICE ALONG THE ANALYTIC WORKFLOW

These indicators are behaviours that would be expected at each stage. Positive indicators are those done in accordance with good practice and negative indicators are the opposite. This is not an exhaustive list. It is intended to be used as a checklist to assess your own or others' output.

Negative Indicators		Positive Indicators
❖Jumps straight to data (skips this step) ❖No effort to further understand customer needs ❖Fails to narrow the focus to something manageable and focussed on directly enabling customer outcomes	**1. Understand Requirements**	✓Questions customer to get to the 'real' requirement ✓Effort made to fully understand customer requirements better before jumping into action ✓Requirements are prioritised in-line with customers needs
❖Jumps straight to data (skips this step) ❖No evidence of thinking about how to approach the problem, next steps not prioritised ❖Plans focused on activities rather than outcomes ❖No hypotheses identified where appropriate ❖Prioritises corroboration/confirmation over disproving which is more definitive	**2. Plan Analytic Response**	✓'Taking a step back' from the problem to determine the best way to approach it before obtaining data ✓Hypotheses identified and plans to challenge hypotheses before seeking to corroborate/confirm ✓Prioritised outcome-focussed actions & next steps ✓Plan documented / communicated / recorded as appropriate ✓Considers task constraints
❖Looking everywhere, or in favourite tools without justification or any indication of prioritisation, economical use of resources/tools ❖Data collection includes irrelevant information or too much redundant information ❖Whole or partial relevant strands of intelligence/activity or datasources are excluded	**3. Obtain Data**	✓Surgical approach to obtaining data, only looking in relevant places for specific things ✓Data collection is focussed on the key question ✓All relevant strands / sources are utilised
❖Content / data inaccurately described and/or mixes different strands of activity ❖Misunderstanding of technical aspects of data ❖Ignores data that can't understand / doesn't fit with existing assumptions ❖No effort made to investigate & understand unexpected data points	**4. Process Data**	✓Content / data accurately described ✓Draws disparate sources of information together while pulling apart different strands of activity ✓Understands technical aspects of data / seeks help from relevant experts if necessary ✓Proactively seeks anomalous data – looks for the 'black swans'
❖More emphasis given to corroborative information, ignores or overlooks data that disproves hypotheses ❖Lack of analytic judgements made ❖Lack of reasoning to back-up conclusions	**5. Interpret Data**	✓More emphasis given to data that disproves/contradicts hypotheses & discriminates between hypotheses over data that corroborates ✓Makes analytic judgements ✓Constructs sound arguments to back up conclusions
❖Unclear verbose communication style ❖Refusal/reluctance to communicate conclusions until more information received / ambiguities have all been resolved ❖Ambiguities not explained / excluded ❖Lacks distinction between 'fact' and analysis ❖Analytic conclusions are not directly related to answering the customer's needs	**6. Communicate Conclusions**	✓Clear concise communication style – easy to follow ✓Provides rationale underlying conclusions drawn ✓Distinguishes between degree of uncertainty around conclusions and level of confidence in conclusions ✓Fully explains ambiguities ✓Distinction made between 'fact' and analysis ✓Analytic conclusions are directly related to customer's needs

E. ANALYTIC INVESTIGATION QUESTIONNAIRE

This questionnaire is designed to guide you through an analytic task. The structured set of questions is intended to be used as a prompt for you to record your findings from each stage of the analytic workflow.

1. Understand Requirements

A. Who are your customers?
B. What are their interests / perspectives are?
C. What does the customer ultimately want to achieve?
D. What are their priorities?
E. Across your customer-base, what are the top x overall priorities?

2. Plan analytic response

A. With the resources & time you have available how can you best help your customer achieve their aims?
B. What are the task constraints?
C. What is the analytic line / hypothesis you going to investigate?
D. What information would corroborate & disprove this?
E. Where do you expect to find this information?
F. What are your options for approaching collection of this information?
G. Which is the most efficient & effective method?
H. What steps do you need to go through?
I. How will you record your 'working out' so that it is auditable / shareable?
J. Which specific database / source will you need to search for the information you need?

3. Obtain data

A. What (source-specific) retrieval method (inc. Query) will provide you with information you require in the most efficient way?
B. What format / output you will receive the results in?

4. Process data

A. What does the data mean? (in plain-English)
B. Was there anything unexpected or anomalous?
C. How have you organised / structured your data in a meaningful way?

5. Interpret data

A. What ways are you able to explain your findings?
B. How well does your original hypothesis explain your findings?
C. Are there alternative ways that could explain your findings better?
D. What are your conclusions?
E. What evidence do you have to support these conclusions?
F. How confident are you in your conclusions?
G. Where & why does ambiguity remains?

6. Communicate conclusions

A. What is an appropriate format to recorded / communicate your conclusions?
B. How have you made the distinction between 'facts' and analytic conclusions clear?
C. How have you expressed your degree of confidence in your conclusions?
D. Does your output focus on satisfying the requirement?