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A Survey of Intelligence Analysts' Perceptions of Analytic Tools

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***Abstract*—This article presents a survey of 278 intelligence analysts' views of fully operational analytic technologies and their newly developed replacements. It was found that usability was an important concept in analysts' reasons for and against using analytic tools. The perceived usability of a tool was not necessarily indicative of its perceived usefulness. Analysts' decisions to recommend an analytic tool to others were best predicted by how usable analysts perceived the tool to be rather than how *useful* they considered the tool to be. These findings have implications for the development and implementation of new analytic technologies in the intelligence community.**

***Keywords*—Intelligence analysis; analytic technology; support systems; usability**

I. Introduction

This paper presents an empirical study of intelligence analysts' perceptions of fully operational analytic tools and their newly developed replacements, in order to explore reasons for using and recommending some technologies but not others. In the first section of the paper, the types of tasks that analysts must perform and the sorts of tools that are available to them are outlined. This is followed by a review of literature on analytic technologies, and the importance of usability. Then, the methods and findings of the present study are presented. Finally, the implications of the findings are discussed, along with directions for future research.

II. Analytic Tasks and Tools

A. *Technologies for the Analytic Workflow*

Intelligence analysts must search for, select, process and interpret data in order to understand a current situation or predict a future one that is of interest to stakeholders making strategic and tactical decisions. In short, analysis is a highly cognitive task [1]. This is made difficult partly because the human mind is limited in terms of attention, perception, memory and processing capacity, and partly because the task can be demanding due to large volumes of (often unstructured) data that can be (sometimes intentionally) misleading.

Over the decades, in addition to providing analysts with training in analytic thinking, efforts have been made to support analysts by providing technology [e.g., 2, 3, 4, 5]. Indeed, there are currently a vast number of analytic tools available for use by the intelligence community. These can be used at different stages of the analytic workflow (see [1]) as they serve a variety of purposes. For instance, there are tools enabling generation of Gantt charts and process maps [e.g., 6, 7] which may be useful at the planning analytic response stage. At the obtain data stage, tools can be used to search for and mine data [e.g., 2, 8]. At the processing data stage, tools can be used to visualize data [e.g., 5, 9]. Tools can also be used to perform network analysis and geospatial analysis [e.g., 10, 11], support argumentation [e.g., 3, 12], support decision-making [e.g., 4, 13], and apply structured analytic techniques [e.g., 14]. Therefore, before tackling the demanding task of analysis, analysts must choose amongst a plethora of tools.

B. *Past Research on Analytic Tools*

There is a large literature on technology-based tools to support intelligence analysis. This includes that discussing the requirements for the design of tools and their evaluation [e.g., 15, 16, 17, 18]. For instance, Elm et al. (2005)[15] devised a list of requirements for the development and evaluation of decision support systems, which they argue are lacking in most analytic tool suites. These requirements include observability, directability, teamwork, directed attention and resilience. However, Elm et al. did not validate these requirements using potential users (analysts).

Scholtz (2005)[16] consulted an unspecified number of researchers and analysts before identifying higher- and lower-level metrics for evaluating technology designed to support intelligence analysis in a number of ways. Higher-level metrics (e.g., quality of and confidence in the product, number of hypotheses explored, ratio of relevant to non-relevant material examined, and time taken) assess analyst process and product quality. Lower-level metrics (e.g., number of relevant documents/number of irrelevant documents produced, correct intra-information relationships identified, quality of system-generated hypotheses, and time spent using each software function) assess whether software features improve that quality. The above metrics are meant to evaluate software that aims to increase effective data search; enhance analysts' prior and tacit knowledge of the data; aid hypothesis generation and reduce confirmation bias; improve human-information interaction; and help analysts to work with big data.

The requirements and metrics for analytic tools do not explicitly include the concept of usability, despite people's preference for user-friendly technology (see [e.g., 19]. Indeed,

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usability can be a key element in the successful transition of new tools from the laboratory into operational use [17]. Although usability is a broadly defined concept, it typically includes reference to being easy or intuitive to use, as well as being attractive. However, Elm et al. (2004)[18] describe some analytic technologies as "user-hostile".

Intelligence analysis software development differs from commercial software development because the users (analysts) rarely decide what to purchase. The classified nature of the intelligence domain makes it difficult to identify and understand requirements. Political constraints also make feedback on software success or failure difficult to obtain [17]. In light of this, it is not unsurprising that there is little research on the factors that might be important in analysts' decisions to select some specific tools to use rather than others.

Researchers working on technologies in the intelligence community have often relied on non-analyst (e.g., student) samples to inform them [20, 21]. Past efforts to study analysts have typically involved small samples (for an exception see [21]). For example, Kelly et al. (2007)[23] used four intelligence analysts to identify evaluation criteria for analytical question answering systems. Clearly, employing small samples of users to inform tool development and evaluation is problematic as it precludes statistical analyses of the responses collected, making it difficult to draw reliable conclusions. In addition, the use of non-expert, unrepresentative samples means that the information gleaned lacks external validity and generalizability. The research described in this paper, therefore, aims to overcome this limitation by capturing the views of a large sample of intelligence analysts and analyzing their responses using relevant statistical tests.

III. The Study

The main aim of the research was to explore intelligence analysts' views of analytic tools. The objectives were to examine (1) analysts' perceptions of the usability and usefulness of analytic tools; (2) their reasons for and against using tools; and (3) their willingness to recommend tools to others. These issues were investigated in the context of both fully operational analytic tools and their newly developed replacements. The latter were comparable to their operational counterparts in terms of readiness for use but were yet to be released at the time of the study. Comparing newly developed tools that will replace fully operational ones enables us to measure the extent to which developers have 'learned' from prior experiences of tool development and implementation.

IV. Method

A. Respondents

Respondents were 278 UK intelligence analysts. Nearly all (93%) of the sample was employed to work full-time.[1] On average, the sample had 6.15 (*SD* = 6.89) years of experience working in the intelligence community. Together, the sample was involved in a wide range of analytic tasks, including strategic and tactical ones.

B. Survey[2]

Respondents were asked to complete a survey that asked about the usability and usefulness of analytic tools; their reasons for and against using these tools; and their willingness to recommend them to others. Responses to the two questions asking about usability and usefulness were each provided on 10-point rating scales (with the higher ratings implying greater usability and usefulness). Responses to questions asking about reasons for and against using a tool were recorded as yes/no, as were responses to the question asking about willingness recommend a tool. Respondents were also asked to provide their demographic details (e.g., work status, and years of experience working in the intelligence community).

The survey questions referred to four specific analytic tools (hereafter called Tools A, B, C and D).[3] All of the tools enabled analysts to search for, and retrieve data. Thus, all of the tools would typically be used at the obtain data stage of the analytic workflow (see [1]). At the time of the research, Tools A and C were fully developed and operational. However, they would be eventually replaced by Tools B and D, respectively. Thus, it was possible to study the four tools as matched pairs (i.e., Tools A and B, Tools C and D).

C. Data Collection Procedure

The survey was advertised a week in advance of data collection on an intelligence organization's intranet. The survey was then available online for a two-week period on the intranet. The survey was individually, self-administered during the respondents' workday, and took approximately 15-20 minutes to complete. Participation was voluntary and anonymous.

D. Data Analysis

Statistical analyses were performed on data from respondents who provided responses on both tools in a pair. This provides a rigorous and sensitive comparison and eliminates the potential confounding effects of respondents' demographic characteristics.

V. Findings

A. Usability and Usefulness of Analytic Tools

When comparing responses to Tools A and B (i.e., fully operational v. replacement), paired-samples *t*-tests revealed no statistically significant difference in respondents' perceptions of their usability (Tool A: $M = 7.17$, $SD = 1.96$ and Tool B: $M = 6.86$, $SD = 2.12$), $p > .05$. However, respondents perceived Tool A to be significantly more *useful* than Tool B (Tool A: $M = 7.32$, $SD = 1.94$ and Tool B: $M = 3.89$, $SD = 2.09$), $t[71] = 10.41$, $p < .001$.

When comparing Tools C and D, a significant difference was found in both respondents' perceptions of the usability and usefulness of the tools. Tool C (i.e., fully operational) was perceived to be easier to use than Tool D (i.e., replacement; Tool C: $M = 7.57$, $SD = 2.14$ and Tool D: $M = 6.49$, $SD = 2.54$), $t[75] = 3.48$, $p = .001$. However, Tool D was perceived

[1] Full demographic data was available for 242 respondents.

[2] A copy of the survey is available from the author.

[3] The tools cannot be identified because they are classified.

to be more *useful* than Tool C (Tool C: M = 5.70, SD = 2.35 and Tool D: M = 6.93, SD = 1.97), $t[75] = 3.66$, $p < .001$.

B. Reasons For and Against Using Analytic Tools

According to McNemar tests, Tools A and B differed significantly ($p \leq .05$) on some of the reasons for why respondents said they might (not) use them. Reasons for *not* using Tool B (the replacement) compared to Tool A (which was fully operational) were because: (1) respondents did not have a unique user account; (2) there was little technical support/training/user manual for it; (3) they did not understand the output it provided; and (4) it was difficult to use.

Reasons for using Tool A compared to Tool B were because: (1) respondents had sufficient training; (2) it was a replacement for a tool they previously used; (3) it was compatible with other tools they use; (4) it contained the data they needed; (5) it allowed them to move data easily between tools; (6) it offered them a new way of looking at/thinking about the data; (7) they could alter the way results were displayed; (8) the output it provided was clear and simple; (9) it was easy to use; (10) it was fast; and (11) it looked 'nice'.

There were few differences between Tools C and D in terms of the reasons for why respondents said they might not use them. The reason for not using Tool D (the replacement) compared to Tool C (which was fully operational) was because respondents forgot it existed; suggesting a lack of in-house marketing of the new tool and a lack of initial uptake.

Tools C and D, however, differed significantly on several of the reasons for why respondents said they might use them. Reasons for using Tool C compared to Tool D were because: (1) respondents had sufficient training; (2) it was a replacement for a tool they previously used; (3) it was compatible with other tools they used; (4) it contained the data they needed; (5) it offered them a new way of looking at/thinking about the data; (6) they could alter the way results were displayed; and (7) it was easy to use.

C. Recommending Analytic Tools

McNemar tests revealed that there was no significant difference between Tools A and B in terms of whether or not respondents would recommend them to others: 88% said they would recommend Tool A and 80% said they would recommend Tool B, $p > .05$. Similarly, there was no significant difference between Tools C and D in terms of whether or not respondents would recommend them to others: 90% said they would recommend Tool C and 83% said they would recommend Tool D, $p > .05$.

Logistic regression models were computed to determine the relative power of respondents' perceptions of the usability and usefulness of each tool in predicting respondents' willingness to recommend the tool to others.[4] The perceived usability of Tool A, B and D significantly predicted respondents' decisions to recommend each of these tools, with 91%, 84% and 91% of decisions predicted correctly by the models, respectively. Respondents' decisions to recommend Tool C were significantly predicted by both their perceptions of its usability and usefulness, with 93% of decisions correctly predicted by the model.

VI. DISCUSSION

This paper empirically examined intelligence analysts' views of analytic tools that were fully operational as well as comparable ones that were newly developed replacements. Analysts' reasons for using and recommending some technologies but not others were also explored. This provides an insight into why some analytic tools are more or less successfully 'rolled out' compared to others. Several findings emerged, and these are summarized and discussed below.

First, the lack of usability can be an important barrier to analysts using analytic tools. The study found that analysts' reasons for *not* using a tool were because there was little technical support/training/user manual for it; they did not understand the output it provided; and it was difficult to use. By contrast, analysts' reported using a tool because they had sufficient training; the output it provided was clear and simple; and it was easy to use. Thus, usability should be a key requirement for the design of analytic tools. While this may appear to be an obvious observation, analytic technologies, beyond those studied here, are often criticized for not being user-friendly [18].

Second, one of the newly developed replacement tools (D) was perceived to be less user friendly than its fully operational counterpart (Tool C), and although one might argue that this simply reflects the former tool's stage of development, it does underscore the problem that developers do not necessarily consider usability as a key requirement for tool development. Rather than viewing usability as integral part to tool development, it is sometimes seen as an 'add on.' Building in usability at later stages of development, however, can be difficult, and may sometimes even be overlooked if time and resources are limited.

Third, the perceived usability of a technology is not synonymous with its perceived usefulness (or effectiveness). Although analytic tools may be considered to be equally usable, they may differ in their perceived usefulness and vice, versa. In the comparison of Tools C and D, it was found that although analysts perceived the newly developed replacement tool (D) to be more useful than its fully operational counterpart (Tool C), they considered the latter tool to be more *usable*. Ideally, tools ought to be both useful and usable, and there should not be a trade-off between these two concepts.

Fourth, analysts' decisions to recommend three of the four tools studied were predicted only by their perceived usability (and not by their perceived usefulness). Most intelligence organizations do not dictate which tools analysts should use, but rather provide them with a selection, thus analysts are at liberty to choose amongst tools fulfilling the same function. Given that word-of-mouth is generally an effective advertising strategy, the decisions to recommend tools purely based on their perceived usability poses a threat to

[4] Sample sizes for the models predicting willingness to recommend each tool were: 235 for Tool A, 74 for Tool B, 195 for Tool C and 188 for Tool D.

the successful implementation of potentially useful tools that are considered by analysts (users) to be less usable.

Finally, other reasons for why analysts chose to use a tool included that it was a replacement for a tool they previously used; it was compatible with other tools they currently use; it offered a new way of looking at/thinking about the data; they could alter the way the results were displayed; and it contained the data they needed. Thus, when designing new analytic technologies, developers ought to consider how tools are currently being used and how new tools either supplant or complement them. In addition, developers ought to ensure that new tools allow users to interact with them in different ways. For example, some analysts might prefer to put data into tabular form whereas others may prefer a graph or chart. Developers also need to be aware of how analysts are currently solving analytic tasks, so new technologies can not only aid analytic thinking, but also improve it.

Given that the issue of usability crops up consistently in analysts' perceptions and experiences of tools, there is a need for future research to better understand this concept from the perspective of the analytic community. Future research could also explore how individual features of this multi-faceted concept determine analysts' perceptions of available tools. As with other recent efforts to move towards an evidence-based approach to intelligence analysis (see [24]), there ought to be an evidence-based approach to analytic technology. The findings of such research can be used to inform the design and development of tools that meet analysts' requirements.

There are, however, some challenges to developing user-friendly tools, even when one has access to large, representative samples of intelligence analysts. For instance, inevitably, users may disagree on what is usable (e.g., more experienced analysts may have different perspectives from less experienced ones, and more tech savvy analysts may differ from the less technologically capable counterparts).

In sum, there is a need for better communication between developers of analytic tools and users (analysts) to guarantee that support systems address the concerns of users and promote the development and survival of the most effective and user-friendly tools. The potentially increased costs and time required to develop such tools may be counter-balanced by the reduced user training and support costs and time, and the lower likelihood of needing to re-develop a tool.

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