A Study of an Intelligence Analysis Team and their Collaborative Artifacts

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ABSTRACT

We conducted a field study of a team of collaborating professional intelligence analysts engaged in a simulated activity in their workplace. We investigated the collaborative nature of the event and how they used artifacts (flipcharts, paper, posters, post-its, projected images, computer displays and representations) to support collaboration. Using activity theory, we analyzed our notes of their collaborative behaviors, our chats with analysts, and photos of artifacts in their context use. We found the collaborative nature of the analysts' activity had a distinct pattern; in earlier stages it is stronger, and later on weaker, and more between analysts and developer-analysts than between analysts. We identify issues in the analyst's current use of artifacts, and identify potential areas where collaboration could be strengthened through technologies that are new to practitioners in the domain, such as large interactive surfaces. Based on our findings we suggest new research directions for the field.

INTRODUCTION

Intelligence analysis work is an important activity and can be critical to security and business success. Intelligence work involves transforming raw data (sometimes large amounts of it) into meaningful and useful knowledge. Traditionally this was done by government and military organizations in the context of national defense, but more recently business intelligence applies similar techniques for competitive advantage. The nature of the work is unique and demanding. There is a very large noise to signal ratio and information can be deliberately hidden or fabricated. The work itself involves making many judgments, which engages both conscious and unconscious processes, and the intelligence that is produced is not always definitive.

We know that intelligence analysis work is both individual and collaborative, but seasoned intelligence analysts have been stressing the need for increased collaboration amongst analysts. For example, Heuer and Pherson [15], former intelligence analysts, are now suggesting that their collection of structured methods for individual intelligence analysis work are also applicable in collaborative contexts. They claim that the use of their collection of techniques in a collaborative context will produce analytic results with reduced cognitive bias while also encouraging stronger team behaviors including cognitive engagement, consideration of greater alternatives, and challenges to assumptions. Hackman [14], also a former intelligence analyst, concurs that more collaboration is needed between analysts, but he also identifies further advantages. He says that strongly collaborative intelligence analysis work not only produces better intelligence outcomes, it also results in the development of the skills of individual analysts and of the team's skills as a whole.

Intelligence analysts use a wide variety of tools in their work. Fjeld et al. [9], building on activity theory, proposed three non-disjoint types of tools: mental, physical and virtual. In the context of intelligence analysis work, mental tools may, for example, be common concepts in the field such as 'tradecraft.' Physical tools are tangible aspects of the world such as keyboards or smartphones. A good example of a virtual tool is a model. Models can be virtual objects, such as a useful digital visualization of a mind map. A physical tool, usually a thing that has physical aspects that can be operated on, is often the physical means by which virtual tools are accessed and used. Tools of all types mediate an activity, connecting the user to real and virtual worlds and to other people. We examine only physical and virtual tools in our study and refer to them as artifacts, primarily for readability.

We worked with an organization that was interested in exploring applications and new technologies to help their intelligence analysts achieve better outcomes and team benefits. They were particularly interested in large interactive surfaces because they thought large high-resolution displays would help with collaboration and big data problems their analysts faced. Large interactive surfaces have not traditionally or regularly been used in the daily work of intelligence analysis teams. By 'surfaces' we are referring to large non-traditional computer-supported displays that allow direct interaction with the surface of the display by supporting multi-touch input and 2D gesture recognition [19]. Surface technologies are changing rapidly, require novel interaction techniques, but also present significant design opportunities for a variety of domains that have yet to adopt them, including intelligence analysis [3]. Large multi-touch, multi-person, sur-

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faces can facilitate collaboration because they bring people in close proximity with one another, so they can see each other's faces, hear each other speak, as well as point and work with information in a way that is visible to all. This can enable communication, which can build team skills, and develop common ground [5].

To investigate the possibilities for new technologies, including large surfaces, we needed to understand work practices. For this, direct observation and interactions with analysts working on an actual investigation would be best, but intelligence organizations and intelligence departments, including the one we worked with, have legitimate confidentiality concerns. We therefore collaborated with our partner organization to create a field study of the highest obtainable validity, which meant an investigation using publicly available data. With our partner organization, we set up a field study involving ten professional analysts. Our goal was to study collaboration within co-located analyst teams[1]. To our knowledge this is the first published study of a full team of professional intelligence analysts at work.

In this paper we present our field study of organic/natural co-located intelligence analysis work with a focus on the physical and virtual artifacts used in collaboration. Our paper describes in some detail how physical artifacts, such as flipcharts, paper, posters, post-its, projected images on screens, and computer displays; and virtual artifacts, such as maps, tables, charts and diagrams are used by analysts to produce analytic outcomes for a simulated concern. Based on our observations we comment on directions for future research work. We found aspects to collaborative analysis work not previously discussed in the literature, such as the early stages of direction-setting and the special role of developer-analysts on intelligence teams. From our new understanding of intelligence analysis we suggest a variety of new research directions for enabling collaboration. These include the surface technologies of interest to our partner organization.

LITERATURE REVIEW

Other researchers have studied intelligence analysts to some degree. Kang et al. [17] studied the process of *student* intelligence analyst teams working on a course project over the course of ten weeks. They concluded that understanding how teamwork occurs is important because "it influences one's whole notion of the process." They observed that student analysts did not collaborate on "data and content," but did collaborate once a week to discuss their status, issues, and next steps. Gotz et al. [12] conducted a 3-hour lab study of 2 intelligence analysts and a researcher analyzing an Enron email corpus, fictitious chat transcripts, and publicly available information on the Internet. The authors encouraged collaboration between the three analysts in the part of their study which required analysts to verify and modify hypotheses. They concluded that support for joint analysis could be improved upon. Bier et al. [2] modified their foraging and sensemaking tools to support co-located and at-a-distance collaboration. They evaluated their modified tools informally in a lab-based observational study, first with two pairs of professional analysts, then in a field study with three other professional analysts, one of whom they were able to observe. They suggested further tool development which would provide support for collaboration around "intermediate work products," a feature not currently supported by many of the tools of intelligence analysis. All of these studies noted the need for more empirical work in the domain.

Other researchers have focused specifically on sensemaking, which is a large part of intelligence analysis work; it is the part that turns a subset of data into knowledge. In 1993 Russell et al. [21] studied sensemakers and focused on making the sensemaking 'operations' of individuals lower in cost and higher in utility. They suggested software tools that leveraged the advantages of interaction for recurring tasks. In 2005, Pirolli and Card [20] used theories of cognition to identify leverage points in foraging loops and sensemaking loops. They identified issues concerned with information overload and attention, and suggested using focus and context techniques when browsing large amounts of information on regular-sized displays.

There have been a number of studies of intelligence analysis work with large surface technology, but without professional analysts as participants. In 2010, Andrews et al. [1] suggested that large surfaces could have positive effects for intelligence analysis. One of their studies with student participants compared an experimental group that had access to a vertical grid of eight 30" displays, and a control group that had a single conventional 17" monitor. Andrews et al. noted that participants performing a sensemaking task in the experimental group had no need to make paper notes of the kind created by the control group. They reasoned that the available space offered the experimental group participants a means of encoding and storing analytic representations in spatial arrangements. A second study revealed that these spatial encodings acted as a form of external memory, a means of atomizing or extracting analytic detail, a means of encoding organizing strategies, and as an aid in integration of process and representation. Subsequently, Vogt et al. [22] studied eight *pairs* of participants (students and faculty) using the same system and doing the same task as Andrews et al.'s study. They showed that collaborating participants experienced similar benefits to the individual participants in the study of Andrews et al. They suggested the large display provided additional benefits because the human mind can encode information that is spatial and textual in parallel, and that many semantic relationships can be expressed spatially (proximity, similarity, and so on). Isenberg et al. [16] studied the nature, value and the means of collaboration for intelligence analysis. They studied 15 pairs of co-located collaborating students on a challenging joint sensemaking task that required accessing and understanding hundreds of documents via a tabletop application. Their task was not unlike the task of our analyst team, and we will spend some time comparing the results of this study with ours, even though the tasks were somewhat different and we observed professional intelligence analysts.

[1] Individual analysts on co-located analysts teams do collaborate with others outside their team, but this is outside the scope of this study.

In our research we have responded to the call from the field and academia for a greater understanding of the collaborative nature of analysis work. We look at the potential for new and existing technologies generally, while also focusing on surfaces.

METHODS

We designed a field study and observed a team of intelligence analysts at work. They set up their own work environment, processes and tools. The analysts worked in a collaborative space within their own premises. This area was equipped with plenty of desk spaces, a projector, post-it notes (poster sized and note-sized), standard computers (most of them with two displays), and networking technologies. The simulated event was carefully designed to provide significant cognitive and technical challenges for the analysts. The realistic aspect was further enhanced by the sincere engagement of the analysis team with the exercise, the contributions of a senior analyst who acted as the team's client, and the large, complex and relevant data sets that we used: a corpus of Enron emails and data available via the World Wide Web. The Enron email dataset is a collection of half a million emails sent over a 3.5 year period capturing correspondence in the final years prior to Enron's bankruptcy. This dataset was released by the US Federal Energy Regulatory Commission (FERD) in 2002. A number of versions of the dataset were published in different formats. Our analyst team began working with a dataset from Carnegie Mellon University [18]. We specifically selected a very large publicly available dataset to ensure we would observe the team grappling with some of the problems associated with large data. In addition to this dataset the analysts also analyzed publicly available data on the Internet.

Ten analysts participated in the study, with one acting as the team's client. Three of the nine analysts on the team were developer-analysts (both analysts and software developers). Of the ten analysts, four were male and six were female. Three had 10 years of experience or more, two had 2-3 years of experience. Five had 1 year of experience or less. The team was comprised of analysts of mixed disciplinary backgrounds, especially in the arts and sciences. This background, experience profile and team size is not uncommon. The analysts used a set of software tools that they had installed on the workstations. Heuer and Pherson have identified 3 types of intelligence analysis teams [15], including traditional analytic teams, special project teams doing real-time analysis, and broader social networks of analysts. What we observed was a traditional analytic team, with a specific task, a leader, and collective responsibility for an outcome, following a process they themselves determined was suitable to their task.

The activity occurred over four non-consecutive days. One experienced analyst served as facilitator, another served as a client, and three were developer-analysts. The developer-analysts were responsible for installing and maintaining all software tools prior to the start of the event. The team chose to use many traditional office software tools, plus some widely available analytic tools, and a few tools to enable collaboration (chat and a software repository). The developer-analysts also provided technical support throughout the activity, and they also conducted their own analysis work.

Though much like their real work tasks, there were some differences between our simulated event and their real collaborative events. This included a new work environment which had been set up for the study, with inevitable differences (e.g. they used open source versions of some of their tools for legal reasons). Also, the team worked in isolation from other departments.

One of us shadowed the analysts, visiting each analyst repeatedly over the course of each day, chatting with the analysts at the beginning and ends of the day, over lunch, or when necessary, when observing. She made notes of both the shadowed analyst's activity and the team's activity over time. She also took photos of artifacts. The notes were transcribed and the photos were inserted into the notes at appropriate locations (at approximately the point in the notes where the photo was taken).

Activity theory provides the overall orientation for the design of this study, the analysis of our data, and interpretation of results. Our data collection methods are similar to Fjeld et al. [9, 10] who also studied co-located collaboration from an activity theoretic perspective, as professional participants were used and a variety of techniques were applied to collect data.

We use Engeström's work on group activity and collaboration [8, 7], applying his model of collaboration to analyze our data. This model is similar to those reviewed by Grudin and Poltrock [13]. We focus on several dimensions of activity theory. The first is the concepts of collaborative activity and the notion of mediating tools, such as physical and virtual artifacts. Collaboration is not simply talking or interacting with others, communicating with others, coordinating actions with others, cooperating with others for individual purposes, nor meeting with others to address common concerns. From an activity-theoretic perspective, collaboration regularly occurs within activity systems, between team members working to achieve a common outcome. Collaboration is the subject-object-subject (mediated) and subject-subject (direct) communication that occurs between team members. Collaboration is regularly mediated by artifacts. Artifacts can become common objects (e.g., a mind map that is shared with the team) through a process called 'common objectification'[2], a term coined by Weber and referred to by Fjeld et al. [9]. It is "... a process by which all (or several) members of a workgroup mutually transfer their individual knowledge, expertise, and experience into a material [or virtual] form. By doing this, they make their materialized knowledge available to other group members." Common objectification is important for explaining the process of externalization (tool creation) in a group context.

The second dimension is the principle of the inter-relatedness of the elements of an activity [9, 10]. This principle highlights

[2] 'Objectification' does not have the negative connotation as in the phrase 'the objectification of a person', which refers to how people can be treated as objects (i.e., objectified).

the co-evolving nature of an activity's elements. We discuss the relationship between collaborative intelligence practices and artifact use and suggest how these might co-evolve with the introduction of new technologies that explicitly support new collaborative practices. This aspect of our work is somewhat speculative, but our intention is to initiate thinking on the link between the development of collaborative practices and collaborative tools such as large surfaces.

The third dimension is learning, meaning the development of an activity. This type of learning, analogous to Hackman's team benefits described in the introduction, is known to occur through the reflective practices of groups. We therefore highlight the reflective practices of our team of analysts in our analysis.

Engeström's model of collaboration provides an idea of the strength of collaborative work. In this model, collaborative activity typically occurs in 'moments', i.e., 'phases' of differing types and strengths. These include, from weakest to strongest, phases where teams coordinate, cooperate, or reflectively communicative with one another:

- "When people 'coordinate their work' each person has a distinct objective and each follows a subtlety scripted role ... which is tacitly understood by others."
- "When people 'cooperate' they share common problems and a common objective while following scripted roles." and
- "When people 'reflectively communicate' they "reconceptualize their own organization and interaction in relation to their shared objectives", and stop following a script. Reflective communication occurs when tensions build and normal work is re-evaluated and developed. This may be to re-assess objectives (the attributes of analytic outcomes) or to adjust other aspects of the activity.

Any of these phases may be mediated by tools.

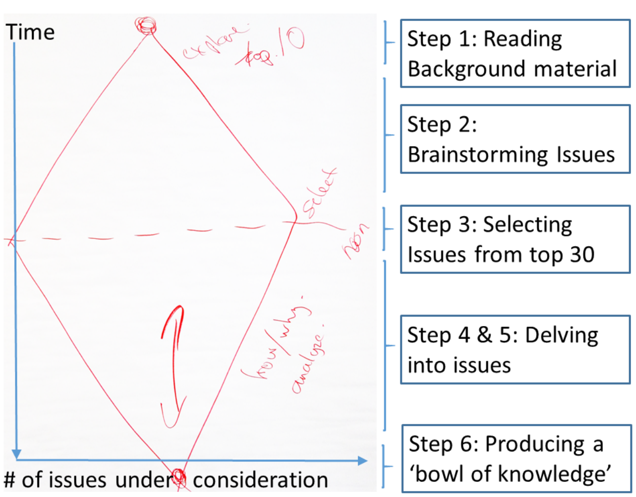


Figure 1. A flipchart depicts the team's 4-day process.

OBSERVATIONS

To begin our simulation, the team's client announced the goal of the study. She said that the analysts should imagine that she "had observed some strange financial transactions" and wanted more background information from them. The 9-person team was tasked with responding to this request. One experienced analyst within the team had agreed to be the team's facilitator. This person determined the structure of the activity prior to the first day of our observations and led the team through a prescribed series of steps as though they had really received this assignment. The facilitator began by explaining to the team that their goal was "to create a bowl of knowledge for the client", i.e., to create a collection of interesting, diverse and potentially relevant analyses. This is a typical outcome for traditional analyst teams, as decision-making based on knowledge is often separated from the process of generating that knowledge.

To begin the process of collaborative analysis, the facilitator used a large flip chart to describe the steps the team would, and actually did, follow (see Figure 1). We next describe what happened in each of these steps.

1) Immersion in the background material. The facilitator provided three preliminary documents: an org chart, a timeline, and a document describing major events relating to Enron. Each analyst spent about forty-five minutes reading this information and making notes. They were looking for anomalies or interesting issues to pursue.

2) Brainstorming issues. Small subgroups of three analysts recorded issues on a board. Interesting investigations were recorded on post-it notes and attached to a team's board. These were then categorized. Categories that emerged included: financial, important dates, social, organizational structure, personal, corporate issues and generic analyses which included keyword searches, temporal analyses of emails sent, word clouds generated from the emails, a generic social map, and a sender-recipient analysis.

3) Selection of best issues. The analysts reformulated into new subgroups to "spread their ideas" more completely across the team. Looking at another subgroup's board, they then selected the ten best issues on that board. A good issue appeared to be one where there was an identifiable anomaly, but also one where an investigation of Enron email or publicly available information, might shed some light on that anomaly. The team facilitator checked to ensure good coverage across all of the categories.

4) Addressing the 'hows' (potential analytical techniques). The facilitator explained he wanted to encourage the analysts to think creatively about techniques and to make an informed choice. Still within the subgroups formed in step 3, the analysts listed 3 analytic techniques beside each of the ten most interesting issues. These techniques were structured practices for analyzing data including building timelines, creating new information repositories, conducting a social network analysis, conducting an analysis of competing hypotheses, and so on.

Steps 1-4 were completed within the first half day. Up to this point the analysts' activity was highly collaborative. In step

5, which lasted two and a half days, the analysts' interaction pattern changed dramatically.

5) Analyzing an issue to understand the 'whys' (why things happened). For this step, each analyst selected an issue from any one of the 30 identified as interesting and headed to a workstation to conduct one of the prescribed analyses. Each analyst had a workstation with one or two displays and they were co-located in cubicles with low dividers. Although they mostly worked individually, to speak to someone else they simply had to stand, or in the worse case, take a dozen steps to another analysts' desk. In general, each analyst aimed to deliver insightful and comprehensive analyses of their chosen issue. However, many of the analysts experienced significant technical challenges.

Extracting relevant information from the CMU email repository proved to be significantly challenging with the resources they had, so at least three other Enron datasets with the same content, but a different format, were also tried. The other data sets that were tried were specially formatted for certain tools, like the R statistical computing environment, an SQL database or Google search. The analysts also used publicly available material to investigate their chosen issue. On mornings two, three and four the analysts had a standup meeting apprising each other of progress or roadblocks with respect to the analysis of their issue. After about 2 1/2 days of work, each analyst had produced an item for the bowl of knowledge. While one analyst used only publicly available material, and another only used material from the email repository, most drew from both sources. During the two day period some of the analysts returned to the brainstorming boards for a new issue if theirs became uninteresting, or if they were blocked for some reason, such as no data on their topic.

We next highlight the work of two analysts (P3 and P4) during this significant and dominant step to give a clearer sense of the individual outcomes produced by the analysts.

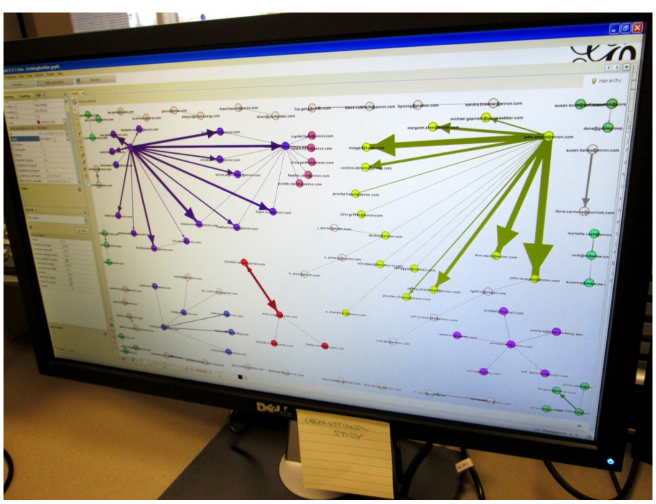
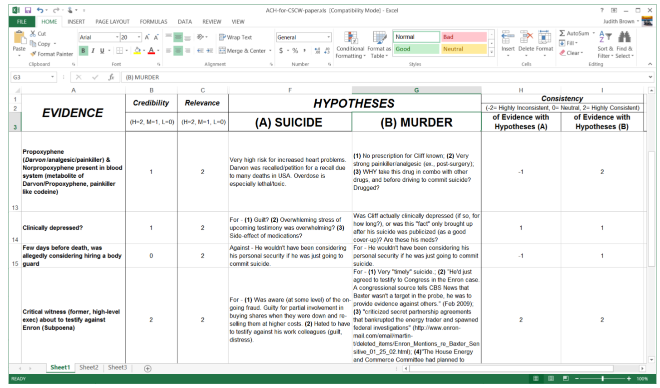


Figure 2. P3's Social Network Analysis (SNA) of Enron employees who met over a drink

P3 wanted to know who socialized with whom at Enron. She completed two Social Network Analyses (SNAs) of "drinking buddies" at Enron (see Figure 2). These were people who met over a drink and who had set the occasion up over email. P3 read thousands of emails that contained the word 'drink', allowing her to identify emails that suggested close relationships. Further investigations allowed her to speculate on the meaning of the invitations (e.g. a business encounter or a sports group meetup). Her analysis helped to provide another perspective of who was talking to whom about business that contrasted with an official Enron org chart. It revealed what P3 called "the real nexus of power at Enron". Her SNA highlighted close relationships that weren't evident from an org chart. P3 periodically cooperated with developer-analysts when doing her work because she needed a bit of help overcoming some technological problems. During this time the developer-analysts and P3 worked side-by-side in the collaborative space, each using their own workstations, but each working towards the common goal of advancing P3's analysis.



EVIDENCE	Credibility (H=2, M=1, L=0)	Relevance (H=2, M=1, L=0)	HYPOTHESES (A) SUICIDE	HYPOTHESES (B) MURDER	Consistency (-2= Highly Inconsistent, 0= Neutral, 2= Highly Consistent) of Evidence with Hypotheses (A)	of Evidence with Hypotheses (B)
Propoxyphene (*Darvon* /analgesic/painkiller) & Norpropoxyphene present in blood system (metabolite of Darvon/Propoxyphene, painkiller like codeine)	1	2	Very high risk for increased heart problems. Darvon was recalled/petition for a recall due to many deaths in USA. Overdose is especially lethal/toxic.	**(1)** No prescription for Cliff known; **(2)** Very strong painkiller/analgesic (ex., post-surgery); **(3)** WHY take this drug in combo with other drugs, and before driving to commit suicide? Drugged?	-1	2
Clinically depressed?	1	2	For - **(1)** Guilt? **(2)** Overwhleming stress of upcoming testimony was overwhelming? **(3)** Side-effect of medications?	Was Cliff actually clinically depressed (if so, for how long?), or was this "fact" only brought up after his suicide was publicized (as a good cover-up)? Are these his meds?	1	1
Few days before death, was allegedly considering hiring a body guard	0	2	Against - He wouldn't have been considering his personal security if he was just going to commit suicide.	For - He wouldn't have been considering his personal security if he was just going to commit suicide.	-1	1
Critical witness (former, high-level exec) about to testify against Enron (Subpoena)	2	2	For - **(1)** Was aware (at some level) of the on-going fraud. Guilty for partial involvement in buying shares when they were down and re-selling them at higher costs. **(2)** Hated to have to testify against his work colleagues (guilt, distress).	For - **(1)** Very "timely" suicide.; **(2)** "He'd just agreed to testify to Congress in the Enron case. A congressional source tells CBS News that Baxter wasn't a target in the probe, he was to provide evidence against others." (Feb 2009); **(3)** "criticized secret partnership agreements that bankrupted the energy trader and spawned federal investigations" (http://www.enron-mail.com/email/martin-t/deleted_items/Enron_Mentions_re_Baxter_Sensitive_01_25_02.html); **(4)**"The House Energy and Commerce Committee had planned to	2	2

Figure 3. P4's Analysis of Competing Hypotheses spreadsheet investigating the death of an Enron executive

P4 made significant progress using one of Heuer and Pherson's recommended structured analysis techniques [15]. She applied the Analysis of Competing Hypothesis (ACH) technique to investigate the circumstances whereby a former high-level strategist of Enron, who was to be a chief witness at the Enron trials, died before being called to provide evidence at the trials (see Figure 3). ACH tabulates hypotheses and evidence as an aid to reducing cognitive biases. She generated two hypotheses: suicide or murder, and used publicly available sources and a small number of emails as evidence. Her analysis advanced considerations on this topic. P4 periodically cooperated with a senior analyst when doing her work. During these occasions the senior analyst pulled up a chair and worked with P4 at her workstation. P4 presented her 'work to date' to the senior analyst from time to time and received valuable feedback from rich discussions that redirected and enhanced her work. They worked in a tightly coupled way towards the goal of advancing P4's analysis.

We have described the techniques used and shown two of the contributions to the bowl of knowledge produced by the team: the ACH analysis and the social network analysis. Other techniques used included the development of a timeline which depicted Enron growth and significant events, the generation

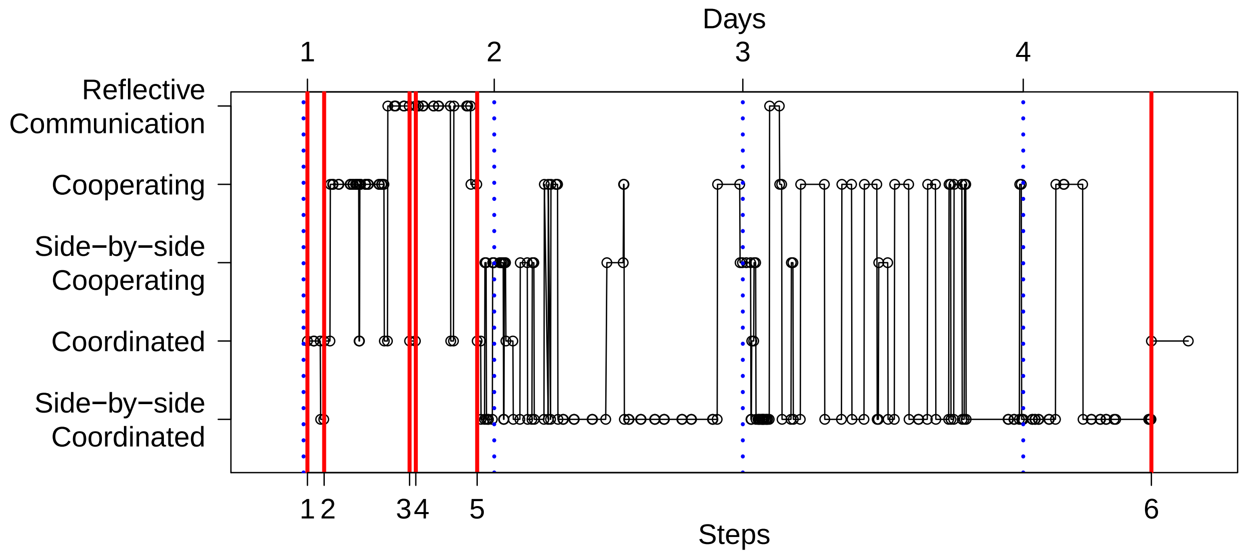


Figure 4. The process of collaboration across time. Solid lines show steps in the analyst's process. Dashed vertical lines show days. Note the absence of reflective communication in step 5, selecting & analyzing issues.

of a sequence of word clouds which showed major topics discussed over time, a content analysis of Enron's whistleblower and 'saboteurs', a content analysis on the corporate culture at Enron, a study of broadband diversification, and a social network analysis of individuals mentioned in a lawyer's email as 'persons of interest' and their involvement with each other and key Enron funds. The results from all 9 analysts were varied in terms of their output and the techniques used, similarly insightful, and completely independent from all other analyses.

On the second half of the fourth day, the analysts completed their analyses and prepared short presentations.

6) Presentation of the 'bowl of knowledge' to the client. On the afternoon of day four, each analyst presented the results of their analysis to the client and other visiting analysts. Each presentation took about 10 minutes. For each analyst, their presentation began with a description of the issue they addressed, the technique they applied, information gleaned, and then their caveats and reservations. They also commented on the value of the technique or tool they used. The client expressed satisfaction with the bowl of knowledge produced by the analysts team, her only reservation being that she would have liked even more financial analyses.

We have mentioned many of the virtual artifacts indirectly in the preceding description (e.g. specific SNAs, WordClouds, timelines, and so on). With respect to physical artifacts, analysts used pens to write on small- and board-sized post-it notes. They made use of large projected images, pointing to items of interest as they spoke. They used single and dual display environments interacting indirectly via mouse and keyboard. Occasionally, to conduct searches of publicly available material, one analyst used her iPhone, and on another occasion an analyst wished for her tablet. Many used paper notepads. Large wall areas were designated for the arrangements of boards arranged with potential issues to investigate and potential analytic techniques to apply.

ANALYSIS

The phases of collaborative analysis work

To get a deeper sense of the collaborative nature of the activity, and to provide more detailed information about it, we analyzed it, using our photo-enhanced notes. Our unit of analysis was a phase of collaborative activity and we used Engeström's model, described earlier, to determine these phases. Each step of the analysts' processes contained many phases.

The notes captured the detailed actions of each analyst because the note taking was continuous and unfiltered. The photos helped us to recall details and context. When the notes were typed up and photos were inserted, each line was numbered in our file. Because note taking was continuous, we could create a rough picture of the activity over time. Roughly speaking, 100 lines of notes corresponded to an hour of activity. We created a spreadsheet that contained columns that indicated the nature of the activity we observed, such as whether different phases were cooperative, coordinative or reflective communication.

For example, when a sub-team was brainstorming we identified that period of the collaborative activity (say from line 50 to line 75) as 'cooperating' because the team members were cooperating on a common objective, i.e., they cooperatively produced the issues boards via brainstorming. When the facilitator brought the team together to describe their next step, we identified that as 'coordinated' because there was no distinct shared objective and shared outcome, but the team members coordinated their actions by each performing their role, which was following the facilitator's lead. When team members talked about their work at a meta level, such as describing their challenges, or the way work could be improved, or they discussed how it should be done, we labeled that 'reflective communication'.

Throughout the entire four days, one researcher constantly recorded who was interacting with whom. Fortunately, team members typically did the same thing at the same time (i.e., while we took notes about one subgroup cooperating, other subgroups were cooperating too; similarly when one analyst was working side-by-side, some others were also working side-by-side). This meant we could shadow analysts in sequence, which allowed us to collect detailed information, but still produce a picture of the entire team's activity.

Our observations leveraged and extended Engeström's model of collaborative processes because we observed new behaviors he did not have the opportunity to see in the context he developed his model: collaborative courtroom activity. In collaborative intelligence analysis activity we observed two additional forms of collaboration. 1) When an analyst was working side-by-side with others in a shared space, but on their own analyses, we called that 'side-by-side coordinated' work. This is because the team as a whole coordinated their actions, i.e., behaved in a way that made side-by-side individualized work possible (mostly by working quietly). 2) When an analyst was working side-by-side, but was doing something for another analyst, as was often the case with the developer-analysts, we called that sort of paired work 'side-by-side cooperative' work. In this case an analyst and a developer-analyst pair (rather than the entire team) were, for a duration, jointly aligned on a singular objective, which was the analyst's current technical issue.

In Figure 4 the horizontal axis indicates time and vertical axes lists the collaborative phases from strongest to weakest. Solid vertical lines divide the activity into 6 steps, and dashed vertical lines divide the activity into days. The diagram shows that roughly speaking, the amount of notes taken was equivalent for each day. The overall shape of the visualization (the pattern of dots and connecting lines) also shows that the nature of the days was not homogeneous. Table 1 shows the phases, typical collaborative practices epitomizing the phase, and the percentage of time engaged in the phase. On day 1 we see the progression through steps 1 through 4 and alternation between coordination, cooperating and reflective communication. On day 2 we see the beginning of step 5 (sensemaking), an initial alteration between side-by-side cooperating and side-by-side coordinated work, followed by a period dominated by side-by-side coordinated work (individual co-located work). Day 3 continues the work on step 5, but shows an alternation between side-by-side coordinated work and cooperating (paired analyst work). There was little reflective communication in step 5, and a great deal of side-by-side coordinated work (a weak form of collaboration). Day 4 concludes step 5 and the presentation of results, step 6.

Social Network Analysis

In another analysis of our notes we present an SNA depicting the interactions we captured between team members (see Figure 5). The thickness of the line reflects the number of collaborations. Each interaction would be one of the types previously described (cooperative, coordinative, reflexive, and so on). We found that P7, the person primarily responsible for the analysts' tools, engaged most strongly with others. Close seconds were P8 and P9 who also had developer-analyst roles. P3 consulted widely for technical and analytic advice. P1 and P6 cooperated on a joint analysis for a time, but the available tools made this infeasible and the initiative was dropped. P4 and P10 cooperated on an Analysis of Competing Hypotheses, and at one point used one display with multiple active windows and two additional displays at the same time. The client (P10), interacted with nearly everyone, but these interactions were always initiated by the client (direction not shown on the diagram).

Phase	Percentage of time engaged in phase, Steps 1-5	Percentage of time engaged in phase, Step 5 only
Reflective communication e.g. Evolving team processes	10%	1%
Cooperating e.g. Paired analyst work	23%	21%
Side-by-side cooperating e.g. Technical assistance	6%	8%
Coordinated e.g. Team standup meetings	10%	7%
Side-by-side coordinated e.g. Individual co-located work	50%	62%

Table 1. Percentage of time engaged in the various phases of collaboration ordered by most closely coupled (reflective communication) to least closely coupled (transition points). Note: Transition phases, not shown, accounted for 1% of the time.

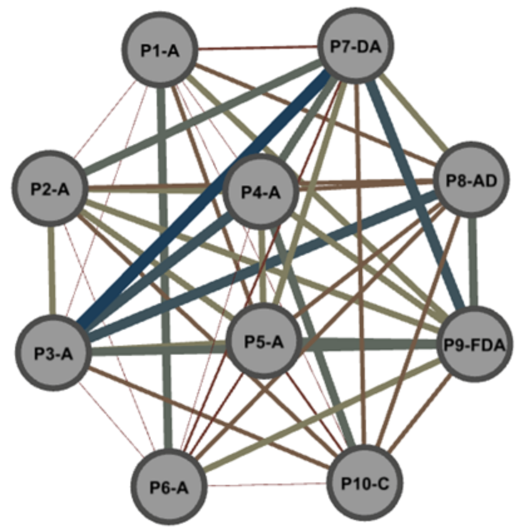


Figure 5. An SNA of analyst interactions in step 5; A=Analyst; D=Developer-Analyst; C=Client; F=Facilitator

Artifact Use

The physical artifacts the analysts used in their work included any regular-sized computer display or analog surface (e.g., pads of paper or post-it notes and so on) that analysts interacted with via direct or indirect pointing or with pens. We examine the use of such artifacts and the preferred mechanisms for interaction.

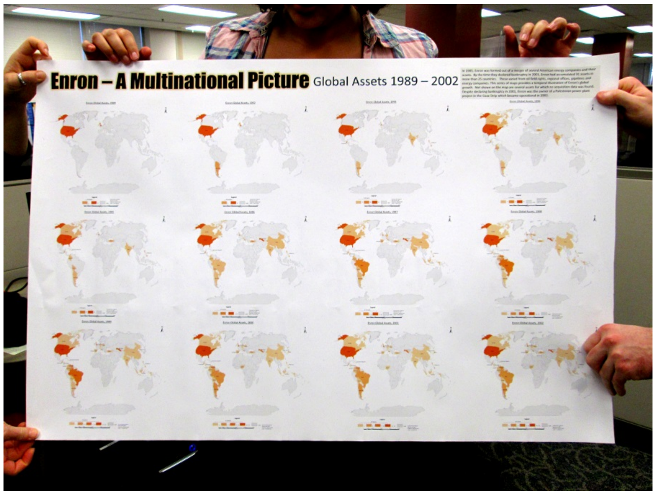


Figure 6. P2's Poster depicting global Enron asset expansions over time.

After day 1 when large paper-based technologies were primarily used for brainstorming, the analysts used single or dual display arrangements with mouse and keyboard, although most would have preferred more displays. Typically one display (or window depending on display space) was used for querying the corpus, one for results, and one for the emerging analysis. Additional displays or windows were usually used for displaying data from web searches. No display space was used for communication within the team (e.g., sharing tips or documents). All analysts used a paper notepad and each kept a post-it note of their issue by their workstation. Use of mobile devices was rare, although the client used her smartphone when collaborating with analysts, and one analyst bemoaned the absence of her tablet in the brainstorming session.

We noticed that physical artefacts with a large surface area could positively enable the work of the team. For example, P2 created a large and detailed poster/map between day 2 and day 3 of the study (see Figure 6). This generated a significant amount of discussion at the daily standup meeting where the team engaged with the map, a valuable intermediary artefact, by pointing and gesturing. This served multiple purposes. Firstly, it exposed misunderstandings about the categories and color codings that needed to be fixed. It also generated a significant amount of new insight and new questions about Enron's global expansion. Similarly, P4's analysis of competing hypotheses advanced significantly when multiple displays were used. A senior analyst who worked with P4 at length and on more than one occasion, regularly used her smartphone to explore evidence. On one of these occasions a third analyst checked out some facts for P4 on Google maps at his workstation.

However, the physical artifacts the analysts used also posed them problems, especially with regard to certain aspects of interaction that generally relate to scaling or limitations of the medium. In this analysis we used our photos and our notes to make a sequence of annotated photos, each depicting an issue that the analysts experienced using physical artifacts. The text provides descriptions of problematic interactions with phys-

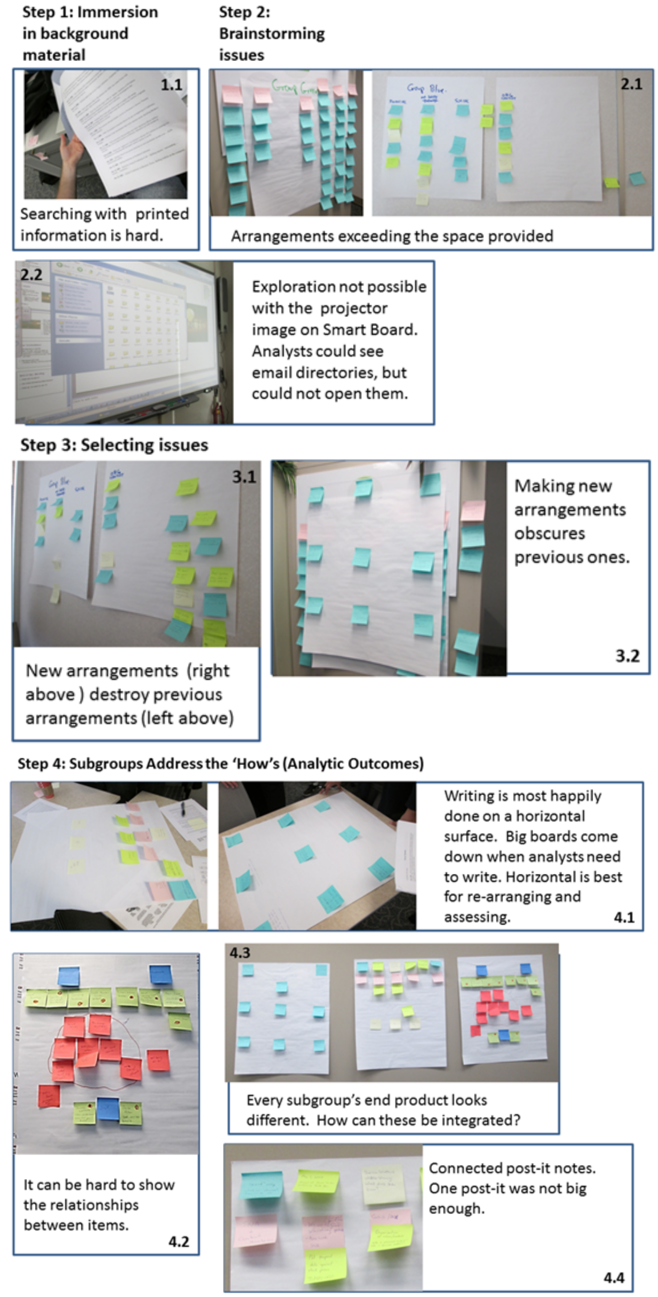


Figure 7. A Pictorial list of problems with the artifacts used by the analysts in Steps 1-4

ical artifacts and the photographs provides an image of the surface. Our pictorial/textual list of problems (see Figure 7) with the physical artifacts used by the analysts in Steps 1 to 4 is organized by time. The detailed analysis for Steps 5 and 6, which cover an additional 11 pages, have not been included. The entire corpus comprises a rich description of the activity, as well as useful statements about physical artifacts and interactivity. We next highlight some findings.

The wrong physical artifact could hinder the work. For example the analysts brainstormed using post-it notes, and, although the post-it notes were flexible, there clearly were some significant drawbacks to brainstorming in this manner. As a very simple example, post-it notes tended to become unglued when analysts took posters down to write on them. More significantly, it was difficult to merge the results of 3 brainstorming subgroups because of differing subgroup conventions, such as color usage. Also, when post-it notes were re-arranged information was sometimes lost (like categories which were written on boards and not on post-its and which differed across groups). They could also not be easily rearranged to make plans or used for situation awareness.

The lack of large physical artifacts was also an issue. For example, one instance of a rich collaborative discussion followed from the presentation of P3's large poster. In contrast, no such team discussion occurred around any of the other analyst's intermediate results, which were never displayed in a large format.

Lack of collaborative applications was a final problem. Two senior analysts attempted to collaborate on a SNA using Gephi social analysis software to investigate a list of a dozen people, and abandoned their attempt because they could not engage in cooperative work that would result in a single analytic outcome. After spending half a day sharing a workstation, mouse and keyboard, they decided to split their problem into two and work in parallel at separate workstations. Having split the problem in two, they had a new problem in that they could not easily coordinate and integrate their work.

The physical artifacts the analysts used presented them with many irksome problems, each one of which took their attention away from the substance of their analysis work and therefore had a negative impact on it.

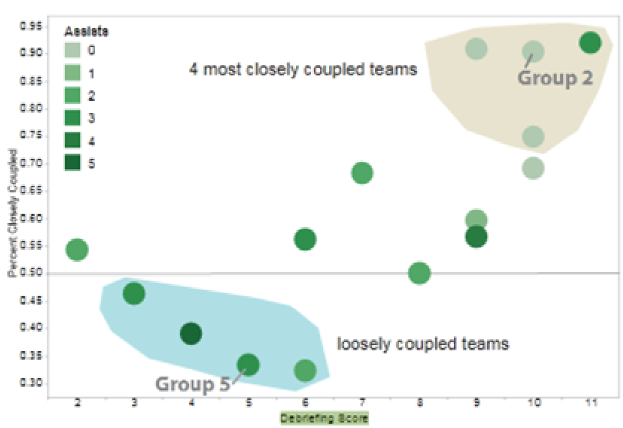


Figure 8. Team performance (x-axis); % of time analysts cooperated (y-axis) (Isenberg et al.)

DISCUSSION

We begin by comparing our results to the work of Isenberg et al. [16], introduced in our literature review. Isenberg et al. focused on the effect of collaboration on correctness in intelligence analysis work. They studied 15 pairs of co-located collaborating students on a challenging joint sensemaking task that required accessing and understanding hundreds of documents via a tabletop application. Their task was not unlike the task of our analyst team, but a critical difference is they had predetermined a correct answer. They found that the more the students worked in a closely coupled way, the better they performed with respect to correctness relative to a known solution. A graph displaying the results of this relationship is shown in Figure 8. The four most loosely coupled teams (pairs that cooperated 30-45% of the time) scored between 3 and 6 for correctness. In contrast, the four most closely coupled teams (pairs that cooperated 75-90% of the time) scored between 9 and 11. The researchers established a correlation between closely coupled work and correctness, and the role that interactive surfaces might be able to play, a result supported by Vogt et al.'s study of student and faculty pairs using a 32 megapixel tiled vertical display[22].

With our data we could estimate how much time our analyst team spent closely coupled. When considering the three most closely coupled categories in Table 1 we can see the team spent 39% of their time closely coupled (10% + 23% +6%). Assuming a comparison between our activity and Isenberg et al.'s is legitimate, our team rated most similarly to Isenberg et al.'s loosely coupled pairs in terms of the strength of the cooperative behavior of the team, suggesting that the team is not very closely coupled when working, and that overall performance may be improved by more team-wide or pair-wise cooperation. Further, if we compare our team's activity from step 5 onward to the behavior of Isenberg's pairs we have a more equitable comparison. In this case, we use only the subset of our data where our team now knows the issue they will investigate and the technique that they will use. This was a given in Isenberg's study. Now we see that they worked closely only 30% of the time (1% + 21% + 8%). However, we do make this explicit comparison cautiously given the differences in the studies, especially since Isenberg et al.'s study used students.

Relative to some of the analyst pairs in Isenberg et al.'s study [16], the event we observed was not strongly collaborative, and we trace this back to the nature of the required collaborative outcome, i.e., the "bowl of knowledge", that did not require a singular result from the team. However, from our observations we speculate that more collaboration is not necessarily always better for professional analysis work, as Isenberg et al.'s study of students seems to suggest. We observed that the analysts worked *individually* in a shared space for a significant amount of time, which seemed to be an established and valuable part of their practice. We think there is a research question to be addressed regarding how much closely collaborative work should be occurring in intelligence analysis in the real world.

Beyond comparing our work with Isenberg et al.'s we also noticed other distinctive team behaviors. From our observations of professional analysts and their investigative practices, we saw particular patterns of collaborative practices emerging. The exploration of their investigative space was initially highly collaborative. Here they searched for anomalies and generated a diverse set of potential issues to explore. They collaboratively narrowed down the issues and identified multiple ways to explore each one.

Their established practice of seeking a bowl of knowledge then led the team into pursuing individual investigations. This step of the work extended over most of the time period. However, this step was not purely individual work. The dominant form of collaboration that we observed involved analysts cooperating with developer-analysts to solve technical problems associated with data and tools. The SNA analysis depicted in Figure 5 illustrates the most common collaboration occurred between analysts and developer-analysts to receive technical assistance. The observational study also showed that this team did not have a process for collaborating with its client. We also recorded two instances where analysts cooperated on an issue, and how in both cases they were impeded by their tools. From these two cases we conclude that 1) splitting and reintegrating larger analytic tasks appears to be something analysts would like to do, but is difficult, 2) it is useful, but challenging, to move between individual work and cooperative work. Despite the fact that the bowl of knowledge requires independent work, there are still opportunities for collaboration. The poster sharing episode indicates that sharing of intermediate results can enable situation awareness, advance individual analysis work, and influence other analyses.

Looking back at Figure 4, we can see that beyond the first day there were few phases of reflective communication, including at the end of the activity. We found this unusual because similar studies of collaborative software developers found many phases of reflective communication throughout the day [4]. These developers regularly questioned whether the software would be completed with the right attributes, and whether they would meet their client's requirements with available resources. In the software world continuous reflective communication practices help keep the work on track and increase the chances the right software will be created.

We also did not observe tightly coupled analytic work on a single issue. While the practice of tightly coupled work might seem less productive than independent work, research has shown that programmers are more productive in pairs than individually, are less prone to making errors, and learn more [11][24]. Researchers have concluded that pair programming is of value because of the complexity of the task (an attribute it has in common with intelligence analysis). Also, the value in pair programming is a consequence of the intermediate-level dialog between the developers that helps to align their understandings. The latter is a process that could also apply to paired or collaborative analysis work.

Further, analysts did not appear to check each other's work. Individual analysts were conscientious and vigilant about their sources, but they did not double check their work with others. Having another analyst check one's work can find errors, and it can also prompt reflective communication about the desired attributes of an analysis (such as thoroughness or rigor) and whether or not these are being achieved. It can also yield cross-person mentoring enabling individual and team benefits.

Comparison to other research

Compared to other studies with professional analysts[17, 12, 2], our study appears to have the highest domain validity with respect to participants, team size and tasks, and observes more natural behaviors for a longer period of time; also it is the only study with the primary purpose of studying mediated collaboration. Like Kang et al. [17], we found a significant amount of separate work occurred within teams; however, their student analysts worked individually in separate places, and our professional analysts worked individually, but in a co-located workspace, where brief moments of face-to-face collaboration were possible. Like Gotz et al. [12] we also observed that support for joint analysis could be improved. However we did not see a lot of joint analysis work (two analysts, one outcome). We saw a joint social network analysis attempted by one pair of senior analysts, but they abandoned it because their tools could not support it. Like Bier et al. [2] we also concluded that support for collaboration around "intermediate work artifacts would be beneficial", based on the positive response of the team to one analyst's poster presentation of a partial analysis.

Compared to other studies on sensemaking, we agree with Russell et al. [21] on the value of interactivity for repetitive tasks, since so much of the work moved iteratively towards a final model, with each iteration's new direction based on the state of the model in the previous iteration. Informally we also have many reasons to support Pirolli and Card's popular model of sensemaking that includes foraging and sensemaking loops, which in our study amounted to work on extracting useful information from the data and work on building an interesting model from the extracted data. All of our analysts did this. However, while Pirolli and Card hypothesized moments of information overload, and issues with attention, our study showed the strongest moments of frustration occurred when attempting to extract relevant data. We hypothesize that the virtual artifacts and techniques the analysts used helped to reduce information overload and issues of attention because, as predicted by activity theory, the virtual artifacts helped to structure their foraging and sensemaking work so that it did not become overwhelming. That said, we do think that larger, higher-resolution displays or more displays, could only help with preventing information overload and issues with attention.

Other research on intelligence work considered the role of large interactive surfaces, but without professional analysts as participants. Like Andrews et al. [1], we saw analysts encoding and storing representations in spatial arrangements, although they saw this with a large number of small documents on an arrangement of 8-displays. We saw analysts arrange post-it notes in meaningful ways, arrange their tools spatially across two displays, spatially structure documents of data snippets and interesting urls, make spatial arrangements of the names of persons of interest and financial funds, create sequences of maps, or tease out sub-clusters within social networks. We concur that space itself is an important tool in sensemaking, but we also see it as being important for planning and directing the work. We also concur with Vogt et al.'s study [22], which concluded that additional display space was beneficial for collaborative analytic work. Our analysts did not have 8 displays in front of them. However, we saw collaborating analysts using smartphones to look up information when working with another analyst at their workstation, allowing the two to work in parallel. We also watched as the technological problems of one analyst were solved at one workstation with dual displays, while that analyst continued working on other aspects of their work at their own two-display workstation. It was not uncommon for four displays to be collaboratively used in this way.

In comparison to all of the research above, we observed a more comprehensive activity than simply sensemaking. It included a significant early phase where the direction of the work was set, where the intelligence analysts selected their own issues in a general area of inquiry, but as a team ensured that there was a broad coverage of topics. There was also a significant step that involved selecting a method of inquiry. Although the physical and virtual artifacts they used were also discussed in other studies, we observed a significant variety and diversity, whereas other studies typically focus on singular artifacts. We also saw a variety of software tools being used in the process.

In addition, we observed that developer-analysts were an essential and integral part of the intelligence analysis team. Their primary role was to support the other analysts, and they brought software development expertise in transforming raw data into more useful forms. They also explored new software tools for conducting analysis, and conducted their own analyses. This kind of work is not reported in other studies of intelligence analysis teams.

NEW RESEARCH DIRECTIONS

Our study was motivated by a desire to learn about collaboration in intelligence analysis work. We were especially interested in the use of physical and virtual tools, and how they might inform research on new technologies, such as surface technology, to support collaboration. We took three different approaches to exploring how new technologies might transform collaborative intelligence analysis activity and the research issues that would need to be addressed.

Our first approach focuses on *process productivity*. We began by exploring the possibilities for improving the mediational tools in the activity across the steps of the process they followed. In step 2 (Brainstorming), subgroups of analysts could have easily categorized issues (e.g. by dragging digital post-it notes into appropriate digital piles), created new digital displays without destroying old digital displays, and created meaningful, integrated and pleasing arrangements of categorized issues. Step 5 (Delving into Issues) constituted much of the time in the activity, and our results suggest several possibilities for improving support. A prominent characteristic of step 5 is the frequent alternation between individual and collaborative work, but there was little support for this. Even being able to display an individual's computer screen onto a large display would help, but technology to allow more fully collaborative interaction would be worth exploring. More specifically, we especially noted collaboration between analysts and developer-analysts, for technical support and exploration of new technical approaches. Even simple screen sharing software might help this kind of collaboration, but better support might be possible, for example allowing capture and annotation. In step 6 (Presentation), new display technology could have helped analysts illustrate connections between each other's artifacts (imagine a large display with analytical outcomes and annotations showing connections between them, all of which could be explored interactively). Each of these suggestions could be explored through research prototypes, and evaluated in terms of the productivity impact.

Our second approach focuses on *process outcomes*. Here we thought about how new technologies and collaborative practices could be introduced into the intelligence domain to have a strong impact on the activity's outcomes. This approach stems from two understandings within activity theory. The first is a focus on the inter-relatedness of elements of an activity and the observation that elements (e.g. tools and practices) co-evolve; the second is a focus on the outcomes of an activity and how the activity itself can be tuned to achieve different outcome attributes. As an example of an existing collaborative practice, we observed the intelligence analysts brainstorming mediated by large posters. This practice ensured the team would pursue interesting irregularities ensuring diversity in the outcome.

However, other collaborative practices could have potentially ensured the final analytic outcomes had other useful attributes. We suggest a few of these now as avenues to explore as a result of our study. Our suggestions are inspired by our observation that collaborative software practices are already a part of the culture, as developer-analysts are necessary team members who are often called on to produce bespoke solutions. We considered collaborative software development practices, such as pair-programming [23] or retrospectives [6] that have evolved to ensure attributes of software outcomes such as program correctness and process improvements. Our suggestions include 1) Joint analyses to potentially increase correctness — large surface application can be used jointly by analysts working together; 2) Ensuring complete coverage of issues of interest — might be supported by software linking analysis efforts to models of relevant issues; 3) Ensuring analyses meets client needs — could be supported by technology to support checking and formative reviews by client representatives; 4) Ensuring analysis does not contain inconsistencies and that it meets explicit or tacit standards — might be supported by automatic checking software or workflow systems that supports analysts cross-checking each other's work; 4) Sharing 'golden nuggets', i.e., data that was particularly valuable — any system that supported situation awareness might improve this. These suggestions could be explored through research prototypes, and evaluated in terms of changes to actual outcomes.

Our third approach focuses on *learning within the process*. In activity theory it is well-established that important learning occurs in cycles of externalization and internalization as team members interact. In the activity we observed, more support could have been put in place to increase the likelihood of individual and team benefits, two secondary outcomes of strong collaborative practice. In the collaborative event we observed, very few team benefits ensued except when team members shared and reflected on their techniques during their presentations. There were also minimal individual benefits (although a few analysts learned new tools on their own, individuals did not explicitly learn from each other).

For the team benefits, development of team skills and coordination strategies, networking and increasing the team's commitment, analysts need to be brought closer together and interact more frequently. In the activity we observed there was a significant amount of side-by-side coordinated work and significantly less cooperative work between analysts beyond the first day. There was also very little reflective communication, a key requirement for experiencing team benefits. We suggest that a balance of side-by-side coordinated work and cooperative work is appropriate for this intense type of work. However, our observations also suggest that more connections between the team members could have benefited the team's development. We saw some evidence of team learning in step 6 (Presentation), where each analyst used a data projector to show the team what they had produced and how they did it. But we felt this might have been more beneficial if it had been done earlier and more frequently, for example with large displays in the normal working environment.

For individual benefits to do with learning, the best way to achieve this is to make it easy for novices and experts to connect. New practices such as working in pairs on a single analysis could help, and new technologies could also be useful. For example, systems of displays that connect experts in a domain with novices in that domain could help enhance a novice's learning (e.g. a novice could shadow an expert on a duplicated display). Other possibilities are face-to-face pair work, perhaps enabled by a shared horizontal surface with half of the display oriented to one analyst and half to the other.

Each of these approaches, though differing in intent, appear to lead in similar directions. One theme appears to be a need for support for moving back and forth between individual and collaborative environments. Another aspect, however, is that the principal focus of attention is not a document or file, or even a set of documents or files, but rather an active workspace. The workspace included desktop arrangements, sets of open GUI windows and command line windows, and an underlying but evolving heterogeneous set of data. Moreover, the software tools involved were themselves diverse and changing, and being used together in an exploratory way. This is what we observed, and we understand this is standard practice: there was no single way of doing analysis, no single software system, and both diversity and evolution of tools were accepted. Yet the need for collaborative support is clear. Large displays and screen-sharing software can provide primitive support, but we suggest there would be great value in going further.

The organization we worked with had been particularly interested in large digital multi-touch displays. We do see potential for these in some of the areas suggested above, for example, for joint work on visual models, for situation awareness, and to facilitate collaborative reflection. However, we also suggest that other collaborative technologies could be valuable. There may also be a role for other surface technologies we have not mentioned, involving tangible interaction or graspable artifacts, especially when an area of inquiry is a geographical region and there is much map-based work.

CONCLUSIONS

We conducted a field study of a team of collaborating professional intelligence analysts engaged in a simulated activity in their workplace. Because the organization we worked with was interested in exploring the possibilities of new technologies to improve collaboration, we investigated the collaborative nature of the event and the analysts' use of physical and virtual artifacts. We analyzed observational data using concepts and models from activity theory.

We created a rich description of the experience of collaborative intelligence analysis work. We observed new aspects of the work not previously reported in the literature. In particular we observed early stages that precede sensemaking. We also observed the important role of developer-analysts on the team. We also saw that analysts themselves carefully chose the methods and the virtual artifacts they would produce, in the context of a rich and diverse software toolset.

We found collaborative intelligence analysis work had a distinct character, with strong collaboration early in the process, and mainly weaker forms of collaboration later on. We found analysts regularly collaborated with supporting developer-analysts, but little with each other, and little with the on-site client. We speculate that the framing of the activity, as the production of a bowl of knowledge, had a significant influence on the degree of collaboration. In their use of collaborative artifacts, we found that analysts used low tech solutions for brainstorming and multiple screens when analyzing. We found significant potential for the use of new technologies, to support productivity through easier work sharing, to support outcome quality through better facilities for checking and situation awareness, and to support learning by aiding reflective communication.

While we analyzed professional analysts, the activity was a simulation using publicly available data and therefore not wholly ecologically valid. Also inter-team collaboration via email, chat and so on, could not be observed in this study. However, our study was suited to its purpose of studying a professional analysis team at work, and it opened up many potential research avenues for not only leveraging new technologies to support collaboration, but also for evolving analytic work itself.

REFERENCES

1. Andrews, C., Endert, A., and North, C. Space to think: large high-resolution displays for sensemaking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM (2010), 55–64.
2. Bier, E. A., Card, S. K., and Bodnar, J. W. Principles and tools for collaborative entity-based intelligence analysis. *Visualization and Computer Graphics 16*, 2 (2010), 178–191.
3. Brown, J., Wilson, J., Stevenson, G., Hack, C., and Biddle, R. *Surface Computing and Collaborative Analysis Work*. Claypool and Morgan,, 2013.

4. Brown, J. M., Lindgaard, G., and Biddle, R. Joint implicit alignment work. In *Proc. NordiCHI 2012*, ACM (2012), 693–702.
5. Clark, H. H. *Using language*, vol. 4. Cambridge University Press Cambridge, 1996.
6. Derby, E., Larsen, D., and Schwaber, K. *Agile retrospectives: Making good teams great*. Pragmatic Bookshelf Raleigh, 2006.
7. Engestrom, Y. *Interactive Expertise: Studies in Distributed Working Intelligence. Research Bulletin 83.* ERIC, 1992.
8. Engeström, Y. Activity theory as a framework for analyzing and redesigning work. *Ergonomics 43*, 7 (2000), 960–974.
9. Fjeld, M., Lauche, K., Bichsel, M., Voorhorst, F., Krueger, H., and Rauterberg, M. Physical and virtual tools: Activity theory applied to the design of groupware. *Computer Supported Cooperative Work (CSCW) 11*, 1-2 (2002), 153–180.
10. Fjeld, M., Morf, M., and Krueger, H. Activity theory and the practice of design: evaluation of a collaborative tangible user interface. *International Journal of Human Resources Development and Management 4*, 1 (2004), 94–116.
11. Freudenberg, S., Romero, P., and du Boulay, B. "Talking the talk". In *Proc. AGILE 2007*, IEEE (2007), 84–91.
12. Gotz, D., Zhou, M. X., and Wen, Z. A study of information gathering and result processing in intelligence analysis. In *IUI 2006 Workshop* (2006).
13. Grudin, J., and Poltrock, S. Taxonomy and theory in Computer Supported Cooperative Work. In *Handbook of Organizational Psychology*, S. W. Kozlowski, Ed. Oxford University Press, Oxford, UK, 2012, 1323–1348.
14. Hackman, J. R. *Collaborative intelligence: Using teams to solve hard problems*. Berrett-Koehler Publishers, 2011.
15. Heuer Jr, R. J., and Pherson, R. H. *Structured analytic techniques for intelligence analysis*. CQ Press, 2010.
16. Isenberg, P., Tang, A., and Carpendale, S. An exploratory study of visual information analysis. In *Proc. SIGCHI*, ACM (2008), 1217–1226.
17. Kang, Y.-a., and Stasko, J. Characterizing the intelligence analysis process: Informing visual analytics design through a longitudinal field study. In *VAST 2011*, IEEE (2011), 21–30.
18. Klimt, B., and Yang, Y. Introducing the Enron corpus. In *First conference on email and anti-spam (CEAS)* (2004).
19. Müller-Tomfelde, C., and Fjeld, M. Tabletops: Interactive horizontal displays for ubiquitous computing. *Computer 45*, 2 (2012), 78–81.
20. Pirolli, P., and Card, S. The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In *Proceedings of International Conference on Intelligence Analysis*, vol. 5 (2005), 2–4.
21. Russell, D. M., Stefik, M. J., Pirolli, P., and Card, S. K. The cost structure of sensemaking. In *Proceedings of the INTERACT'93 and CHI'93 conference on Human factors in computing systems*, ACM (1993), 269–276.
22. Vogt, K., Bradel, L., Andrews, C., North, C., Endert, A., and Hutchings, D. Co-located collaborative sensemaking on a large high-resolution display with multiple input devices. In *Human-Computer Interaction–INTERACT 2011*. Springer, 2011, 589–604.
23. Williams, L., and Kessler, R. R. *Pair programming illuminated*. Addison-Wesley Professional, 2003.
24. Williams, L., Kessler, R. R., Cunningham, W., and Jeffries, R. Strengthening the case for pair programming. *IEEE Software 17*, 4 (2000), 19–25.