ORCHESTRATING SENSEMAKING: INVESTIGATING THE SENSEMAKING PROCESSES AND ITS ENABLERS AT THE DUTCH POLICE

Completed Research Paper

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Abstract

With the increase in the amount of data available to organisations, we hypothesise that the sensemaking process has changed compared to descriptions in earlier literature. In this case study, we investigate intelligence analysis at the Dutch Police, contextualizing it as a fundamental sensemaking process. The results reveal top-down, bottom-up, and ad hoc sensemaking processes at three organisational levels. Schematisation through predefined structures appeared to be a crucial part of the sensemaking loop. We found that for intelligence analysis, schemas are not just a tool but also a product of the sensemaking process. Further diverges from existing literature were found in the absence of a recurrent search for information, but rather appearing as a constant information flow that produces additional information needs. We have not observed an evident reliance on machine learning techniques in specific sensemaking processes. Finally, we identified 24 enablers for sensemaking, spanning data, software, organisation, and process domains.

Keywords: sensemaking, enablers, intelligence analysis

1 Introduction

Intelligence and its associated activity *intelligence analysis* are both terms with a broad definition. At its core, intelligence analysis is the process of creating an understanding of information (Mangio and Wilkinson 2008). This information can take various forms, such as raw data, events, and evidence, but may also contain gaps and inconsistencies. Intelligence, derived from information, is transformed in order to align with the customers unique environment (Krizan 1999). The role of an intelligence analyst involves interpreting information, a task characterized by "connecting the dots" and formulating hypotheses (Lefebvre 2004). Intelligence analysis is essentially a sensemaking task. While this process has been explored in numerous studies, most of the relevant work dates back about two decades. Pirolli and Card (2005) have described the process in an influential empirical study on intelligence analysis. Much has changed since this work; particularly the advent of Big Data makes the need for an understanding of sensemaking greater than ever (Russell et al. 2018).

The surge of Big Data has led to an increase in the volume, variety, and velocity of data (Choi, Wallace and Wang 2018). This increase in available data would suggest that the process of sensemaking has also become more complex, since there is more data to make sense of, which is not necessarily easy to interpret. Different technologies can help organisations to make full use of the opportunities provided by large amounts of data (Oussous et al. 2018). These technologies can aid in data collection and analysis, and possibly automate some tasks in the analysis processes.

This study goes beyond existing research by investigating multiple sensemaking processes in a single organisation and how these interact. In our case study at the Dutch Police, we explore how organisations can harness extensive amounts of unstructured data, and the role of sensemaking in the analysis of this information. Furthermore, we identify the factors that foster sensemaking in this particular sensemaking ecosystem.

2 Theoretical Background

In this section, we will review existing research on the sensemaking process.

2.1 Sensemaking and representations

The basis for research about sensemaking in an information science context is the *Learning Loop* which was introduced by Russell et al. (1993). In the study, they generalised the tasks of making sense of large amounts of information. Russell et al. (1993) define sensemaking as *the process of searching for a representation and encoding data in that representation to answer task-specific questions*. One of the contributions of the study is the identification of the *Learning Loop* process as a part of sensemaking. This model contains three stages: a *Search for representations*, where sensemakers search for a way to represent the data, including the creation of a method to transform data to the representation; *Instantiating representations*, where the sensemaker searches for related data and encodes it in encodons, instantiated representations containing the retrieved information that aid in answering a task-specific question; and *Shift representations* where the sensemaker analyses residue, data that does not fit the representations, to check if the representation should be expended. The results of the learning loop are encodons, which are used for presenting the findings of an information processing task.

Pirolli and Card (2005) build upon the work of Russel et al. (1993), by applying cognitive task analysis to the process of intelligence analysis. They propose a sensemaking model that transforms six forms of data (listed in increasing order of effort and structure): (1) *external data sources,* containing raw data; (2) the *shoebox*, which is a smaller set of relevant data that should be processed; (3) the *evidence file,* containing parts of information from the shoebox; (4) *schemas*, representations that aid in making conclusions; (5) *hypothesis,* unconfirmed conclusions with supporting arguments; (6) and the *presentation,* which is the end product which can be used to communicate findings.

In more recent work, Kang and Stasko (2014) used Pirolli and Cards sensemaking model to analyse intelligence analysis in a field study. Although the model provided useful guidance, they found a difference between the way they observed how analysts work, and how this is described by Pirolli and Card. The main difference was the non-sequential working method of the analysts, which was observed in their field study, but hardly covered by Pirolli and Cards model.

2.2 Intelligence analysis

Intelligence analysis, the process of creating an understanding of information (Mangio and Wilkinson 2008), is essentially a sensemaking task. One model that describes this process is the cyclical model by Krizan (1999), who presents a model for intelligence analysis in a government and business context. The process can be described in five main steps (Zhang and Soergel 2014): The process starts with *Planning/Tasking* which is driven by an intelligence need from an end-user; afterwards, information is *collected* for this need; this information is then *processed* where information from the collection is further filtered; this information is then *analysed* where analysts interpret the information and make sense of it. Based on the found information, an information report is *produced*. Afterwards, the report is disseminated to the users, which results in (further) requirements and feedback. Recently, the work methods of intelligence analysists in the Big Data age have been compared to sensemaking, highlighting the large amount information an analyst must monitor (Kane et al. 2023). They describe the challenge of monitoring a round-the-clock information stream, where sensemaking must take place in shifts relying on collaborative sensemaking.

2.3 Cognitive sensemaking

A model that has been constructed based on combining different existing sensemaking models is created by Zhang and Soergel (2014). In their work, they continue their comprehensive model of the cognitive processes of individual sensemaking, which was earlier introduced in (Zhang et al. 2008, Zhang and Soergel 2009). One of the main features of the model is that most activities can be reached from most other activities. The model describes the process of making sense of data to build an internal or external knowledge structure. New in this model is the differentiation between a *data gap* and a *structure gap*, where both are the result of the *identification of gaps* activity. A *structure gap* is handled by searching for relations and patterns in the found data. The *data gap is* solved by looking for specific data and fitting it into the previously built structure. Both gaps are part of two loops consisting of *seeking for data, fitting data into structure,* and *identification of gaps* for the data loop; and *seeking for structure, building structure,* and *identification of gaps* for the structure loop. Further differentiations can be made between the loops, namely exploratory search during a search for structure and a focused search in a search for data (searching *for* sources vs searching *in* sources). Like the model created by Pirolli and Card (2005), the activities can be executed top-down or bottom-up, starting with structures or data respectively.

2.4 Enabling factors

While at the time of writing we did not find any literature describing factors that enable (or inhibit) sensemaking, we did find such factors for Big Data analysis. A case study by Sejahtera et al. (2018) describes the enablers and inhibitors of effectively using Big Data. Malaka and Brown (2015) have performed a case study that lists the challenges implementing Big Data analytics. Two literature reviews present the critical success factors of Big Data (Walls and Barnard 2020, Al-Sai, Abdullah and Husin 2020). Lastly a case study by Gao, Koronios and Selle (2015) combined data from 60 case studies to find critical success factors of Big Data categorised per step in the process. These five studies present factors in technical, organisational, process, and human context.

3 Research Method

We conducted a case study to examine the intelligence analysis operations of the Dutch Police. The Dutch Police, consisting of ten regional units and one national unit, employs a workforce of 63,000 fte. For this case study, we investigated intelligence analysis inside the national unit as well as in several regional units. The case study is an *embedded single case study* (Yin 2013), consisting of three embedded cases each representing an analysis process that is occurring at different places in the organisation. The embedded cases for the case study are:

- Case I: Investigation analysis. Every unit in the police has multiple large-scale investigation teams. Each team investigates a specific criminal case and consists of approximately 15 detectives. Of interest are the one or two analysts who are part of the team. These analysts work to create overviews and insights of information produced by the detectives.
- Case II: Security analysis. Each unit also has multiple security analysis teams working on a specific criminal phenomenon. In these teams, information from investigations and police officers on the streets is monitored. The analysts inside these teams work on creating insights based on the monitored information.
- Case III: Strategic analysis. Every unit also has strategic analysts looking into a criminal phenomenon on a higher level. Their insights aid leadership in setting strategies.

These different levels of analysis also form the different embedded cases in this study. The aim of our case study is to describe the typical instance in a *contemporary study* (Yin 2013), which entails that we are looking at the current everyday work method of analysts. For each embedded case, multiple interviews are conducted. Interviewees include employees who currently work as analysts, but also as other related roles, such as managers, or IT administrators.

Details about the intelligence operation are collected through semi-structured interviews with actors involved in the intelligence process. The interviews are conducted as semi-structured interviews. All interviews are recorded after informed consent is obtained.

3.1 Data collection

We conducted 17 semi-structured interviews to gain insight into the intelligence operations of the Dutch Police. To get better insight into the intelligence analysis practice and how it is positioned in the organisation, we have interviewed analysts, as well as team leaders and intelligence employees who work closely together with analysts. A full list of interviewees can be found in Table 1. All interviews were recorded and transcribed.

ID	Role	Case
1	Case Analyst	Investigation Analysis
2	Information coordinator	Investigation Analysis
3	Case Analyst	Investigation Analysis
4	Tactical Analyst TGO	Investigation Analysis
5	Operational Analyst TGO	Investigation Analysis
6	Team Leader	Investigation Analysis
7	ICT Administrator	Investigation Analysis
8	Former Team Leader, now Product Owner	Investigation and Security Analysis
9	Former Security Analyst, now Product Owner	Security Analysis
10	Security Analyst	Security Analysis
11	Security Analyst	Security Analysis
12	Security Analyst	Security Analysis
13	Senior Intelligence	Security Analysis
14	Manager Implementation New Analysis Workflow	Security Analysis
15	Security Analyst	Security Analysis
16	Researcher	Strategic Analysis
17	Strategic Analyst and Innovation Manager	Strategic Analysis

Table 1. Overview of interview participants with their identifier, role, and case.

3.2 Data analysis

The qualitative data collected from the case study are coded in NVivo and analysed in an inductive manner using the *general inductive approach* by Thomas (2003). This approach allows to "develop a model or theory about the underlying structure of experiences or processes which are evident in the text" (Thomas 2003 p. 2). We generated the first themes driven by our research objective: to identify processes, actors, products, and systems. For this case study, these include *analysis activities*, *analysis duration, data sources, analysis software,* and *other people in teams.* Our main themes are divided into sub-themes, including the type of tasks found for analysis, and the different products that were mentioned as being the result of sensemaking. Further reading allows us to derive lower-level codes with more detail, after which the category system is redefined further. To allow us to derive the enablers of sensemaking, our coding schema also has the top-level themes of *enablers* and *inhibitors*. These in turn contain sub-themes representing the factors that were mentioned by the interviewees. Table 2 presents an excerpt of our coding scheme, illustrating one example. The complete coding scheme can be found in a longer report of this study (Blaauw 2023).

In the within-case analysis, the results from the data analysis are analysed for each embedded case (i.e. investigation, security, and strategic analysis). In our cross-case analysis that follows, we compare the found processes with each other. Combining the findings from the study allows us to identify the general sensemaking process, as well as the enablers of the sensemaking processes analysed.

Top-level theme	2nd level sub theme	3rd level sub theme	Example quote
Analysis activity [An activity in the sensemaking process]	Investigation analysis [Analysis to aid a specific crime investigation]	Schematising [Adding structured or unstructured information to a schema]	"I often start making a diagram in Analyst Notebook, so that you can immediately plot the people and the phone numbers and addresses, so you know what belongs together." (IV2)

Table 2. Excerpt of our coding scheme.

4 Findings

In this section, we present three analyses: (1) *Investigation analysis*, where the analyst supports a criminal investigation; (2) *Security analysis*, where analysts look at a specific criminal phenomenon; (3) *Strategic analysis*, which is supported by scientific research and contributes to determining strategies or to directing policing efforts. We conclude this section with a cross-case analysis.

4.1 Case I: Investigation analysis

Investigation analysis takes place inside large-scale criminal investigations. Each unit has multiple large-scale investigation teams, consisting of approximately 15 detectives and one or more analysts, who are responsible for providing insights into and overviews of the investigation. Throughout the investigation, detectives produce and collect information through activities such as observing and interrogating subjects or tapping phone lines. This information is then stored in the investigation database and forms the basis for analysis performed by the analyst.

Analysts typically start with reading information in the investigation database, which contains mostly textual information about the case such as reports and statements. One manager explains the task: *You will have to go through all texts if you want to extract the information. That takes the most time. And that also applies to telephone calls and the like"* (IV2). While the analyst is reading the information, they filter information and decide whether to schematise the information. This schematising includes the building of a relational schema and that of a timeline. Relation schemas contain entities (e.g. suspects, vehicles, phones, and other goods), properties of these entities and relations between these entities. Timelines typically include, but are not limited to sent messages, phone calls, location history, information from CCTV footage, and official statements.

Analysts may also have to look further into the entities that are described in the reports from the detectives. For example, an entry in the investigation database can contain the names of other persons. An analyst can search for information about that other person in the police systems. This information can then also be included in the schema. Throughout the investigation, an analyst can also describe information needs if they find that information is missing in the investigation. Detectives in the investigation team can then retrieve more relevant information by, for example, internally searching in police systems, or externally deploying an observation team.

During the investigation analysis process, further analysis occurs on the data that is available to the analyst. This is the most ad hoc activity in the process, in the sense that it does not follow a standard process. The product of the analysis can be general insights about the investigation or specific answers to questions asked by leadership. Specialised analysis tools can help with these different types of analysis, by combining the information that has been collected in the investigation. One analyst gives the example of ad hoc analysis: *"At some point, the question was asked: what time of day can we best deploy an observation team? For that, I made a graph showing which days had the most criminal activity. So, we found that it was best to deploy on a Wednesday because that is when he is most criminally active. Those kinds of things are part of the investigation."* (IV3)

Sometimes, a tactical analyst is also involved. who manages the hypotheses and scenarios during an investigation and works closely with the investigations leadership team. One tactical analyst describes their role as follows: *"Your role is to keep an overview of the investigation, to really think based on hypotheses and scenarios, to be the critical note within the VKL, and to prevent tunnel vision."* (IV4)

The process of creating hypotheses and scenarios is aided by a mind-mapping application that allows for the creation of a deep tree where nodes can have properties. The mind-map is based on a template that is uniform across the police organisation. These templates contain an initial set of hypotheses, which differ per type of crime. For example, in the case of murder, these are natural death, lethal accident, suicide, or murder. Information from the investigation database, containing collected information for the investigation, is read and included in the mind-map as supporting or disproving facts for a particular investigation. The mind-map is then further expanded with more sub-hypotheses, which are again linked with evidence. The template also contains some subtopics that should be filled in by the analyst, such as a rough timeline of events.

None of the interviewees mentioned specialized Big Data analysis techniques. This does not mean such techniques are not being used by the police (cf. Schuilenburg and Soudijn 2023). For example, dedicated police IT teams work on making various (big) data sources, such mobile devices seized by the police, accessible and searchable using machine learning. However, such specialized techniques are not ubiquitous in the organisation and do not form a standard component of investigation analysis.

4.2 Case II: Security analysis

The second type of intelligence analysis is security analysis. While investigation analysis is concerned with a specific investigation into one or more subjects, the security teams look at criminal *phenomena*. Each team is focused on a specific phenomenon – or as it is called within the police – a theme. Examples of such themes are synthetic drugs, cocaine, human trafficking, criminal organisation structures, and CTER (Counter-Terrorism, -Extremism and -Radicalisation). The processes of security analysis differ between regions and themes, but in general, we can distinguish between two types of processes in security analysis: the monitoring process and the analysis process.

4.2.1 Monitoring process

This process consists of monitoring information that is automatically brought up by a reporting tool. One analyst describes how the incoming information is part of their process: "*I, as an analyst, also keep up our workflow, which means that I am also monitoring the incoming reports in [reporting system]. [...] This includes a report from a neighbourhood police officer about a small street dealer who is arrested with 300 grams of cocaine under the saddle of his scooter, as well as a lab that exploded on some farm where a person got killed. [...] We look through them and decide on which are interesting for us*" (IV10). The incoming information is then read and reviewed to check if it is relevant. If deemed relevant but containing some unclear specifics, the employee can look up more information in the police systems. Sometimes it is also useful to contact the original reporters, such as the police agents on the streets who encountered the situation. Lastly, the information is structured and stored in the database shared with the team. This structuring activity is comparable to a schematisation step, where the goal is to structurally store the data so that it can be more easily used for further analysis.

One manager describes how the automated search can help find hidden types of crime: *"We have also developed a proactive scan, so we can proactively query all our systems on a daily basis where we check for possible signals of human trafficking. We found that human trafficking can be hidden in many other situations, where it is not always evident that it concerns human trafficking... We found that many signals of human trafficking are really hidden in our own systems"* (IV14)

Teams may have specialised methods for structuring the information that is monitored. The structuring methods are created to fight relevant criminal organisations as effectively as possible. One example of such a method is *crimescripting*, a method of labelling different actors in a criminal organisation, which allows for a more complex social network analysis. Combining the network with results of earlier interventions, targets can be identified that have the most potential to disrupt the criminal organisation.

4.2.2 Analysis process

The second relevant process in security analysis is the analysis process. This process contains little schematisation because during the monitoring process data is already stored in a structured fashion. One analyst describes that a small network analysis is relatively straightforward: *"If we created a good basis, and collected and structured information already, well then of course it doesnt take that long. But it is also dependent on how in-depth the analysis needs to be. If it is a flat analysis looking for a leader in an organisation, and you want to know what the relations are, and what they are currently doing, these kinds of things, well that doesnt have to take longer than half a day to get the first insights."* (IV15)

Analysis can start with questions from leadership, out of interest of the analysts themselves, or by needing to do planned tasks. Products of security analysis differ widely. Sometimes products can be relatively straightforward to execute, while other products may be more complex and include specific details of the analysed crimes. For example, for a phenomenon overview of synthetic drugs, the report includes findings about the sources of the chemicals used, which criminal organisations are active, which chemical processes are used, and whether the markets are intertwined with other criminal markets.

For complex security analyses, specific knowledge is needed about a phenomenon. An example of this is an project within the CTER theme that focused on the growing sovereign-movement. This movement involves people who are of the opinion that they are not a citizen of the country and think they are not required to adhere to the local laws. This analysis requires domain knowledge, as one analyst describes: *"You must read up on other sources, so absolutely not only the police systems. You have to understand where the movement originated and why."* (IV12)

While Schuilenburg and Soudijn (2023) show that Big Data tools for security analysis, such as a data warehouses and applications that support centralised access to relevant sources, are available at the police, again no specific mention of these tools was made in the interviews.

4.3 Case III: Strategic analysis

Another form of analysis that happens at the Dutch Police is strategic analysis, sometimes conducted in the form of scientific research. This type of analysis is often executed by criminologists and occurs in all units. Comparable to security analysis, strategic analysts are subdivided into themes.

A strategic analysis project starts based on an idea from the analysts or based on an information need by leadership. The information needed by leadership, however, is not a concise analysis goal, so further clarification is needed. One researcher describes this process as follows: *"...they are never, or let me put it better, not always able to articulate their question or problem very well. They will say: Yes, just look at everything of everything. Well, that is not always possible. So, you often must take them by hand, and that is often a process in which you must talk to each other several times. "* (IV16)

Depending on the analysis goal, the project starts with a search towards suitable data sources. One researcher describes that experience helps them to know which sources are available since it is not clear to all analysts which information they can use. Sources for this analysis can be diverse, examples are decrypted criminal messages by criminals; interviews with experts inside the police organisation; internal questionnaires; expert meetings; and social media analysis.

Researchers can also use information from earlier investigations in their analysis. This can however have challenges: *"You can really spend hours on it. Because for every investigation it lists all mutations, all investigative powers used, all permissions, all decisions... And that is a gigantic amount of work, so for strategic analysis it actually ends very quickly."* (IV16)

How the data analysis takes place is highly dependent on the type of strategic analysis that is being conducted. Some strategic analysis goals ask for complex tools, such as in the case of geo-analysis where mapping tools are essential. Others can be more straightforward, where the analysis is a numerical analysis. For quantitative analysis, statistics are not always used. A researcher describes the challenges with statistics: *"Usually, I do it as little as possible because the data... as I said... if the input is already flawed, I can still apply a very nice statistical analysis to it, but then, yes... you're really taking a kind of double risk."* (IV16).

The results of strategic analysis are presented in different manners. PowerPoint presentations can be created to present information directly to relevant stakeholders. The results of the research can also be presented as scientific papers. Sometimes the researcher also (co-)authors a book that will include the findings from the research. One researcher describes that approximately half of their work can be published, while the other half is for internal use only. Within the police organisation there is a desire for reports to be short and concise. In practice however, this is a challenge for analysts, because shortening reports can remove relevant information. Stakeholders often call for the findings of strategic analysis to be presented as infographics to be more easily digested.

Various statistical and Big Data analysis techniques may be used in strategic analysis. One example is the use of social network analysis and simulation to study the effects of criminal network disruption (Duijn, Kashirin and Sloot 2014). However, because strategic analysis is so varied, the usage of such techniques cannot be said to form a standard step in the sensemaking process.

4.4 Cross-case analysis

In this section, the findings from comparing the results from the three different cases will be discussed. A further analysis follows, which presents the enablers of sensemaking.

4.4.1 Sensemaking and sensemaking ecosystem

Comparing the modelled processes in each of the cases allows for a generalisation of the analysis process at the Dutch police. This generalised model is shown in Figure 1. Six common activities can be found: (1) *Filtering*, analysts either get data from the information flow or find it themselves. Not all information is relevant for the analysis, so information is filtered. (2) *Searching*, if an analyst needs more information for their analysis, they can search for more information. When the information is not in the existing systems, the *information-need* product is produced, which can lead to more information being provided to the analyst. (3) *Reading*, if the information is unstructured, the analyst will read through the information in order to create an understanding. (4) *Importing/ Converting*, if the data is structured, the analyst may need to convert it before it can be analysed. If relevant to other analyses it can also be added to the schema, if it is an *Ad hoc* analysis, the data will be analysed directly. (5) *Schematisation*, the structured or unstructured information can be added to a schema the analyst is managing, the schemas are a form of structured storage, such as timelines and relational schemas. These schemas can already be a product of the analysis. (6) *Analysing,* the last activity is analysing the information that has been collected either directly or through the created schema. The results of this activity are insights that are relevant to the specific analysis task.

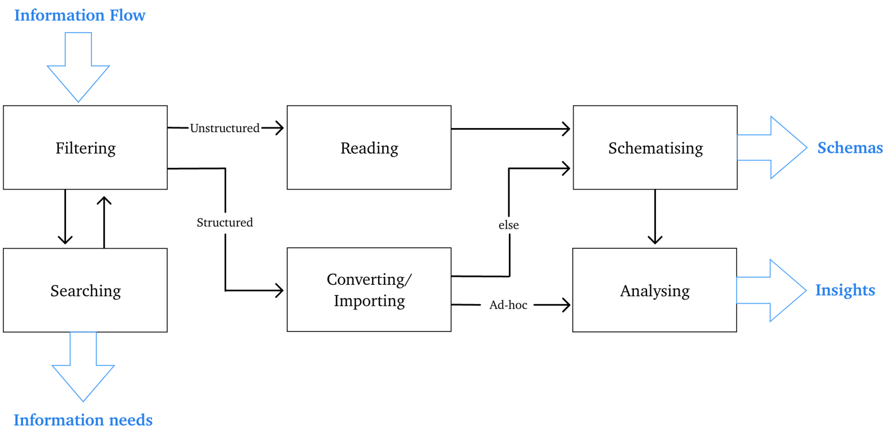

Figure 1. A generalisation of the sensemaking processes found.

Notable in this case study is that the embedded cases are not fully isolated and interact with each other. The different sensemaking processes inside the Dutch Police work together to form a sensemaking ecosystem.

The information flow in the sensemaking ecosystem is shown in the graph in Figure 2. The graph shows how the different analysis teams structure information from the source systems, and how the structuredness and the amount of information about a specific case change in this effort. In the top-left corner, the source systems are displayed, which includes the investigation databases. During investigation analysis this information is schematised and filtered after which it is stored in the analysts analysis environment, following line A in the figure. In this transformation, the amount of information is reduced and the structuredness increases. For security analysis, the source systems are queried to return a subset of information as part of the information flow (line B). This information is then filtered and stored in a structured manner (line C). For the strategic analysis, the analysis is question-driven, meaning that the relevant data has to be searched for, this is represented by line D. Note that security and strategic analysis all use data from multiple investigations in their analysis, explaining why the amount of information about a specific case is decreasing, while the total amount of information is not necessarily less than in a criminal investigation.

Also notable is that we did not find direct evidence of the use of Big Data techniques or AI systems being used at scale in the sensemaking process. We know that such techniques are being used to manage the information flow and support the Searching and Filtering activities, but typically they are implemented and used not by the analysts who perform the sensemaking, but rather by specialized IT and Data Science teams that respond to the information needs of these analysts. Our interviewees are not experts in the field of data science and may therefore not be aware of this.

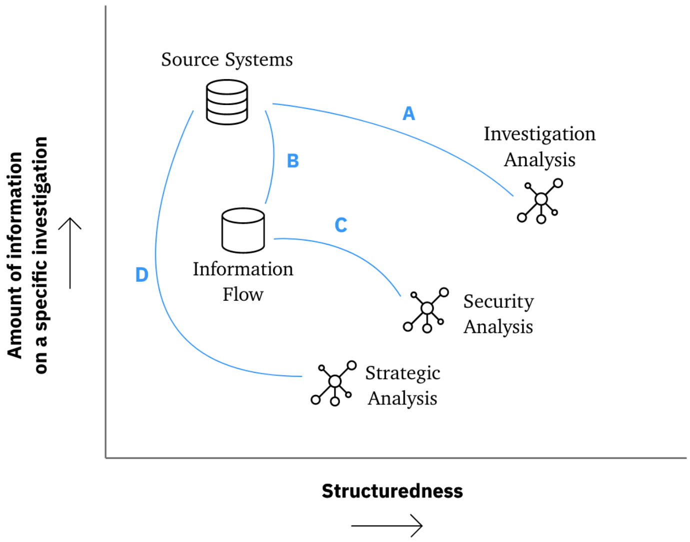

Figure 2. A graph representing how information is structured and reduced across the different systems in the sensemaking ecosystem.

4.4.2 Similarities and differences

Comparing the sensemaking process found in the analysed cases, allows us the discuss the similarities and differences between these. Activities that occur in all three analysed cases are filtering, reading, schematisation, and analysis. Together, these activities form the basis of sensemaking. Another common occurrence among the two of our cases is the presence of an information flow. Analysts often work on monitoring this information flow. In investigation analysis, this information flow is a simple feed of information that is produced by the team. But for security analysis this includes a complex automated querying system that brings up potential reports that are of interest and require further analysis.

Some differences can also be found between the studied cases. The analysed cases have an increasing order in analysis project complexity and analysis project size. Projects in investigation analysis are relatively short, while security and strategic analysis have projects that take multiple days or months to finish. Also, in investigation analysis the small projects are more ad hoc, while security and strategic analysis projects are more formal, and include the activity of clarifying the analysis task they will work on.

Another difference is the initiator of the analysis, differing between being driven by data (bottom-up) or by questions (top-down). The analysis on the level of investigation analysis is driven by data that is supplied by the detectives. In earlier phases, the analyst is primarily working on maintaining this information flow, in the later phases an analyst has more time to initiate their own analysis. In investigation analysis, even when the task is initiated by leadership, it can have a data-centric viewpoint. In such cases, the question can be to ask the analyst to look at the data from an intercepted phone. For strategic analysis, the analysis is often driven by questions of the leadership, searching for the relevant data in the process. Security analysis is a combination of both, because there is a constant monitoring flow being bottom-up (data-driven). However, the found schema is then used for top-down questions.

4.5 Sensemaking enablers

In our case study, we have spoken with many analysts and investigated how sensemaking takes place in the police organisation. With the information obtained from the interviews, we can furthermore derive the factors that enable sensemaking. Enablers can also be found by describing the inverse of problems that analysts are currently experiencing. The enablers are presented in four categories: (1) *data-based enablers* relate to the to-be-analysed data; (2) *software-based enablers* relate to the systems that analysts use to analyse the data; (3) *organisational enablers* relate to the qualities of analysts themselves, and how analysis is organisationally structured; and (4) *process-based enablers* relate to the sensemaking process.

The following **Data-based enablers** have been found: (1) **High data quality**, the to-be-analysed information must be of high quality, this includes the accuracy of textual information. (2) **Easy data integration**, data that is available in a structured format should be able to be used in all relevant systems. (3) **Clear input rules** help increase the structuredness of information and can lead to fewer errors in the source data. (4) **Automated searching tools** can help bring up relevant pieces of information for the sensemaking task, it can also be beneficial to be able to search through non-textual data such as pictures. (5) **Easy data sharing**, sharing data between teams where sensemaking takes place can provide the other team with useful information. (6) **Availability of rich data sources**, in the studied context is beneficial to have a diverse set of data available on the subject you are investigating. (7) **Availability of data catalogues**, sensemakers might not be aware of which data is available to them, a data sources list can help with this. (8) **Data source mutability**, in some cases an analyst might analyse data that is incorrectly entered in the source system, if an analyst can correct the information in this system, it can prevent errors for other analysts.

Regarding the software a sensemaker uses, the following enablers have been found: (1) **Continuous IT maintenance,** systems should be maintained so they keep functioning correctly for analysis, (2) **Fast software speed**, mutation and analysis of information should take little time. (3) **Availability of software catalogues** can make sensemakers aware of what specialised tools they can use for their analysis. (4) **Complex visualisation and analytical tools** enable the analysis of more and a wider variety of information. (5) **Software intuitiveness** makes it easier for sensemakers to use software. (6) **Regularly using systems** can prevent sensemakers from losing their dexterity with software.

The following organisational enablers have been discovered: (1) **Collaboration between sensemakers**, can help sensemakers by having others check their method and it can also give sensemakers insights about how to perform other analysis. (2) **Collaboration between information producers** can help the sensemakers question information from the producers to create a better understanding. (3) **Domain knowledge and specialisation** allow a sensemaker to perform a more detailed analysis. (4) **Critical thinking skills** can help the sensemaker to question the information they are analysing and reflect on the analysis they are performing. (5) **Leadership that facilitates**, leadership should facilitate the sensemaker to perform complex analysis. (6) **Technical knowledge** can help a sensemaker utilise (complex) analysis tools, (7) **Data knowledge**, a sensemaker should know what the context is of the to-be analysed data, so it can know how to interpret it.

Lastly, we have found the following enablers of the sensemaking process: (1) **Clear task descriptions** make sure the analysts know what is expected of them. (2) **Standardisation of processes** can improve the efficiency and accuracy of sensemaking. (3) **Systematic hypothesis generation,** using a method for creating hypotheses and linking them to evidence can help more effectively evaluate them.

The enablers of sensemaking in an information context have not been described in earlier literature. Even though this area has gone overlooked in the literature, there are several studies on the factors that are beneficial for Big Data (analytics). Comparing our findings with enablers in this field allows us to highlight novel contributions to the literature and offers insights into the potential overlaps and distinctions between the identified enablers in these two domains. In Table 2, the found enablers are mapped to five other studies, which were introduced in Section 2.4, that looked at enablers, challenges, and critical success factors of Big Data. Note that because the mapping is made between enablers in two different fields, the relationship entails similarity, not equality.

Enabler	**Sejahtera et al. (2018)**	**Malaka & Brown (2015)**	**Walls and Barnard (2020)**	**Al-Sai, Abdullah and Husin (2020)**	**Gao, Koronios and Selle (2015)**
High data quality	Poor data quality (inhibitor)	Data quality; Data integrity	Data	Data sources	High data quality
Easy data integration	Data silos (inhibitor)	Data integration		Access to sources	Combine different data sets
Clear input rules				Data standardisation	
Automated searching tools					
Easy data sharing			Information sharing	Data sharing	
Availability of rich data sources			Data	Data sources	
Availability of data catalogues					
Data source mutability					
Continuous IT Maintenance					
Fast software speed	Adequate system capabilities			Flexibility and scalability of applications	
Availability of software catalogues					
Complex visualisation and analytical tools			Infrastructure and analytics platform	Technology, infrastructure, and applications	Visualisation
Software intuitiveness					
Regularly using systems					
Collaboration between sensemakers					
Collaboration between information producers					
Domain knowledge and specialisation					
Critical thinking skills		Skills shortage	Analytical skills of the employees	Human capability	Analytical skillset

Leadership that facilitates	Champions		Managerial skills		
Technical knowledge	Lack of technical skills (inhibitor)	Skills shortage	Technical knowledge	Human capability	Technical skillset
Data Knowledge				Data documentation	
Clear task descriptions					
Standardisation of processes					
Systematic hypothesis generation					

Table 2. A mapping of the enablers identified in our case study with factors that have been found to be important for Big Data (analysis) in earlier studies.

5 Discussion

In this section, we discuss the scientific implications, practical implications, and limitations.

5.1 Scientific implications

In this study, we have analysed the intelligence analysis processes inside the police and looked at how sensemaking takes place. This study is the first we could find that looks at multiple sensemaking processes in one organisation, and how they form a sensemaking ecosystem together. In this section, we discuss how the sensemaking processes found compare to those described in existing work. We will conclude this section by reflecting on the found enablers of sensemaking.

5.1.1 Top-down, bottom-up, and ad hoc sensemaking

The sensemaking processes found in our case study are executed as a mixture of ad hoc, top-down (goal-driven), and bottom-up (data-driven). Many studies highlighted the ad hoc nature of sensemaking (cf. Kang and Stasko 2011, Krizan 1999, Zhang and Soergel 2020, Chin, Kuchar and Wolf 2009). Pirolli and Card (2005) describe sensemaking as an "*opportunistic mix*" between a bottom-up and top-down processes, which is consistent with our findings. Each embedded case we analysed has a predominant direction: investigation analysis involves the schematisation and analysis of information provided by the investigation team, which is a bottom-up process. Security analysis consists of two processes, a bottom-up monitoring process where relevant information is structured and a top-down process where the structured data is analysed. Strategic analysis uses top-down processes that are driven by questions from leadership or the analysts themselves. Note that this classification as bottom-up or top-down regards the primary direction of analysis. In our case study we found that, for the bottom-up processes, the created schemas can lead to questions which can call for the search for more information, reversing the direction of the process.

Furthermore, we found that the process on the investigative level consisted of a smaller project cycle, making the projects more ad hoc. Comparing this to the *cyclical intelligence model* (Krizan 1999), we found the intelligence analytics process includes less *planning/tasking* and *requirement/feedback* for bottom-up (data-driven) analysis compared to top-down analysis (goal-directed). Overall, we found that investigation analysis mainly involves just a sub-set of activities, since their individual analysis products are smaller and more informal. In contrast, the security and strategic analysis products are more time-consuming and include more activities mentioned in the cycle.

5.1.2 Schematisation through predefined structures

In our study, we found schematisation to be a crucial part of the sensemaking loop, which is in line with findings from Jolaoso, Burtner and Endert (2015). Pirolli and Card (2005) have described schematisation as being part of their sensemaking process. The found schematisation activity is comparable with the *learning loop* proposed by Russell et al. (1993) and the *structural information seeking cycle* of Qu and Furnas (2008). In both models, a representation is built, which is similar to building a schema. The two models include a concept related to structuring information, namely *searching for good representations* in the learning loop, and *structural-information need* in the structural information seeking cycle. These concepts are focused on the need for structuring ideas. In the schematisation activity we identified in our case study, the search for structured ideas was not mentioned as being part of the process. This can be explained by the fact that, in general, investigation analysis projects overlap in the types of entities, relations, and properties that are available. For example, most investigations have persons, vehicles, goods, and locations as entities, which all have a standard set of properties. This suggests the analyst already knows an adequate representation to schematise the information and does not need to develop or find this structure.

New in our depiction of the sensemaking process of the Police, is the explicit delineation of *schemas* and an *information need* as outcomes of the process. Earlier literature has described the role of schematisation to be an intermediate step in the process (Pirolli and Card 2005), only aiding in the creation of subsequent insights from sensemaking. However, within the context of the investigative sensemaking process uncovered in one of our cases, we observed that one of the main products of the analysis performed were schematisation products. These schematisation products took the form of a timeline of events and a relational schema of the subjects involved. The same holds for the *information need product*; although the *Cognitive Sensemaking Model* does mention a *data gap* as an intermediate concept in the process (Zhang and Soergel 2014), our case findings reveal that this *information need* is not only an intermediate step, but a tangible product of the whole process. Subsequently, the team will try to address this information need by seeking additional relevant information.

Another addition to our sensemaking process description compared to earlier studies, is the incorporation of structured data analysis. Innovations related to Big Data have led to an increased diversity in data types. Consequently, the information available to analysts extends beyond mere text. Our case study reveals that investigation analysts routinely engage with structured data derived from sources such as trackers and intercepted phones. This information also plays a crucial role in sensemaking because it serves as an additional source of information. In the sensemaking model outlined by Pirolli and Card (2005), it is not mentioned how structured information fits in the process. In contrast, our sensemaking process explicitly describes how structured information is handled. We introduced the activity of *converting/ importing* information to facilitate the analysis. Moreover, structured information may also be incorporated into the *schema* through the *schematisation* activity.

5.1.3 Handling the information flow

In the sensemaking process that we revealed in our case study, we identified several important concepts absent from the existing literature on sensemaking. The first concept is an *information flow* in bottom-up sensemaking. This is a flow of information that ought to be analysed. This flow can be provided by team members, or stem from an automated system searching for relevant data. We suggest two reasons why this phenomenon has been overlooked in earlier studies. First, technological innovations have facilitated real-time information feeds incorporating complex filtering algorithms. These technologies might not have been available during earlier sensemaking research. Secondly, the information feed emerges as a result of a sensemaking process that is integrated into an investigative organisation. In contrast to an isolated project-based sensemaking process where this infrastructure may not be in place, the Police is an organisation where sensemaking is essential and pervasive across the entire organisation. Within our case study, the reciprocal interactions between the sensemaking process and the environment in which the organisation operates are reflected in the *information flow*. The found *information flow* is in line with the found stream of high veracity data in the research from Kane et al. (2023). While they highlight how the information stream influences the collaborative aspect of sensemaking in the form of having to hand over work when working in shifts, in our research we continue on how this information flow influences the individual sensemaking process.

Finally, in our case study analysis, we focused solely on what happens outside the analysts mind, i.e., what activities they are performing and what systems they are using. Nevertheless, a notable discrepancy emerged between our findings and the *Cognitive Sensemaking Model* (Zhang and Soergel 2014). While the model posits that the resulting structure can be either an internal or external representation shaped by the *identification of gaps* and *seeking for data activity*, our study reveals an additional dimension. In the sensemaking process we observed, there exists a data feed requiring analysis without the necessity of active searching. Even when the model considers an internal structure, such as a narrative in criminal intelligence analysis, our study underscores that the story in the analysts mind is not only created through *seeking for data* or *seeking for structure* to fill *data gaps* or *structure gaps*. Rather, it also incorporates data provided by detectives that warrants consideration. We argue that there is a missing activity that tests the current story in the analysts mind on new data, not necessarily motivated by a *data gap*.

5.1.4 Enablers

Based on our case study, we also identified a list of enablers for the sensemaking found at the Dutch Police. We did not find any papers listing enablers that link to sensemaking in an information science context. One of our found enablers is confirmed by statements made in papers that looked at sensemaking. Chin, Kuchar and Wolf (2009) state that *multivariate visualisations* can be beneficial, comparable to our *complex visualisation and analytical tools* enabler.

In Section 5.1.4 we have compared our findings with enablers found in a Big Data research context. We found that especially our enablers relating to data quality, integration, and availability are relevant in Big Data. The same holds for software capabilities, analytical skills, technical knowledge, and management being important factors for Big Data.

5.2 Practical implications

Our research gives a high-level overview of the processes that are related to intelligence analysis at three levels within the Dutch National Police. This research can be used to get an understanding of these analysis processes. Additionally, this research can help with creating an understanding of the policing context in which these processes operate. Unique to this context is the large amount of textual information that is available. In turn, the process descriptions can be used to find opportunities for improvement inside the Police organisation. Possible improvements include the usage of Big Data Analysis techniques. At present, such techniques do not form a standard component of the sensemaking processes within intelligence analysis, and a better understanding of these sensemaking processes may contribute to the development of new Big Data techniques.

Our found enablers describe the factors that are beneficial for intelligence analysis. The police, and anyone relying on analysis of unstructured information, can learn from these enablers. They can be implemented to aid in the value extraction from information that is available to an organisation.

5.3 Limitations

In this section, we reflect on the limitations of this research. Participants in our case study have been selected through convenience sampling and participation in the research was voluntary. This could lead to a bias where only the working methods of analysts were studied of those who are okay with others looking into it. The findings of the case study are furthermore limited by the honesty of the interviewees and the accuracy of their answers. We have tried to mitigate these limitations by interviewing multiple persons within each case, as well as different roles.

The police context in which the case study was conducted is highly complex with a unique sensemaking ecosystem. This context is part of all three embedded cases of our case study, which makes generalising the results outside of this context complex. We do argue that our results may be generalised to other policing organisations worldwide and other investigative organisations where the sensemaking of large amounts of textual information takes place.

A last limitation is that the coding process was performed by one researcher. Even though the coding was done in multiple iterations to enhance reliability, the inherent subjectivity of (inductive) coding remains a potential constraint on the results. To mitigate this limitation, the resultant code underwent thorough discussion and validation with other researchers involved in the project.

6 Conclusion

In this study, we have investigated the intelligence analysis operations inside the Dutch Police to study how sensemaking takes place. We have described how intelligence analysis is executed within three different analysis levels inside the Police. By generalising the results of the three individual cases, we were able to present a generalised sensemaking process in the cross-case analysis. The model describes how we found sensemaking takes place in the organisation. We have also described how sensemaking can vary between the higher and lower levels of analysis. Inside the police sensemaking is a combination of six activities: *filtering*, *searching*, *reading*, *converting/importing*, *schematising* and *analysis*. Products of sensemaking are *information needs*, *schemas*, and i*nsights*. For sensemakers there can also be an incoming *information flow*. The data collected in the case study also allowed us to investigate the enablers of sensemaking in the organisation. We have listed a set of 24 enablers in the categories of data, software, organisation, and process.

Our case study revealed that the schematisation activity sometimes happened multiple times on the same source information. We call for research on how the reuse of schemas can be improved, so others can use it in their sensemaking processes. An interesting challenge related to this is the structural storage of this information, in a way that it can easily be reused, but also queried and searched.

In our research we have focused on how sensemaking takes place externally, looking at the activities of sensemakers, their products, the systems they use, and the greater context in which sensemaking takes place. We have however not investigated the processes that occur in an analysts mind. We therefore call for future works on the internal sensemaking processes. This research area is specifically interesting with the further rise of AI and other black-box algorithms. Lastly, other research can investigate the sensemaking enablers in other organisations in order to validate our found enablers and test their generalisability.

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