An analysis of expertise in intelligence analysis to support the design of Human-Centered Artificial Intelligence

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***Abstract*—Intelligence analysis involves unpredictable processes and decision making about complex domains where analysts rely upon expertise. Artificial Intelligence (AI) systems could support analysts as they perform analysis tasks, to enhance their expertise. However, systems must also be cognisant about how expertise is gained and designed so that this is not impinged. In this paper, we describe the results of Cognitive Task Analysis interviews with 6 experienced intelligence analysts. We capture themes, in terms of their decision making paths during an analysis task, and highlight how each theme is both influenced by expertise and an influence upon expertise. We also identify important interdependencies between themes. We propose that our findings can be used to help design Human-Centered AI (HCAI) systems for supporting intelligence analysts that respect the context of expertise.**

I. Introduction

In this paper, we describe Cognitive Task Analysis (CTA) interviews with 6 intelligence analysts, applying the Critical Decision Method [1] [2], that captured their thought processes as they recognised and responded to situations, performed analysis, and delivered outputs. We extend a model developed by Gerber et al. [3] that describes the way that criminal intelligence analysts make decisions through a combination of intuition, 'leap of faith', and insight. Our extended model was used to capture, cluster, and collate broad themes described by the analysts and to provide a foundation for Emergent Themes Analysis (ETA) [4] [13]. For each of the broad themes, we considered sub-themes that reflected the different processes involved and the meaning or significance in terms of cognitive reasoning, such as the requirements for expertise or experience to deliver the processes effectively.

Intelligence analysts operate in challenging and uncertain environments, where they need to consider both the analytical requirement and the situation at hand when performing analysis and delivering outputs. The decisions made by analysts are intellectually demanding and do not typically have a clear or obvious answer. Instead, they are informed by experience and expertise combined with their awareness of the situation. Intelligent systems have the potential to aid analysts when making decisions, for example, by speeding up their analysis, improving accuracy, or focussing their attention upon the most important information. Our CTA findings demonstrate that there are interdependencies across otherwise distinct analytical processes where expertise or experience is developed and drawn upon to meet the cognitive requirements for effective analysis. We present these findings diagrammatically, to describe how AI systems can support analysts where expertise is required, while being cognisant of how expertise is gained.

In this paper, we describe how our findings can be used to guide the development of Human-Centered Artificial Intelligence (HCAI) solutions, which support decision making paths to reach insights. We define HCAI as AI-based systems that amplify and extend human perceptual, cognitive and collaborative capabilities, through a deep understanding of the human. We propose that, for a system to deliver HCAI, the interdependencies between cognitive requirements must be factored into the design. We identify cognitive requirements by considering, across the themes involved in the analysis process, the aspects that are influenced by expertise and those that influence the development of expertise. By drawing this distinction, we capture the potential for AI systems to support analysts where they aid the use of expertise, whilst appreciating the needs for systems to be designed not to impinge upon the development of expertise. We describe some examples.

II. Related work

Defence Intelligence provides intelligence assessments is support of policy-making, crisis management and the generation of military capability [5]. Intelligence assessments are produced as a result of intelligence analysis. Intelligence analysis is not a straightforward process [6]. It involves unpredictable environments where available information can be vast, ambiguous, and have many gaps that may or may not be possible to fill [7]. There are also complex customer requirements with various influential factors.

While the many various tasks and approaches performed by an analyst are difficult to describe succinctly, past research provides a model that captures an analysts decision making path. Gerber et al. [3] consider criminal intelligence analysis and present an adaptation of the Recognition-Primed Decision model [8] and the decision ladder [9]. This model presents how experts recognise patterns, use their intuition to deal with uncertain data and start lines of inquiry, then explore those lines through analytical processes to derive insights and eventually arrive at a claim.

Artificial Intelligence (AI) systems have the potential to support analysts throughout this process, for example, by helping them to recognise interesting patterns, or assisting them when performing analysis techniques. However, intelligence analysts operate in high risk and high consequence domains where there is a need for analysts to be accountable for their decisions [10]. Analysts must be able to explain the evidence that underpins a claim and articulate why they have taken a particular decision. To do this a system must provide explanations for outputs together with transparency of the underlying system processes, so that a user can inspect and verify the goals and constraints [11]. If it is interpretable, then the system can be described as HCAI that is explainable, comprehensible, useful and usable [12]. The framework for system transparency, presented by Hepenstal et al. [11], shows that an understanding of context is crucial for developing interpretable systems. In order to capture the context appropriately it is necessary to develop a deep understanding of the human cognitive requirements through comprehensive analysis.

III. Study

We conducted Cognitive Task Analysis (CTA) interviews with 6 experienced intelligence analysts, of similar seniority, working in the domain of Defence Intelligence. We initially interviewed 7 analysts, however, one analyst had a significantly different role to the others. We have therefore included data from only 6 analysts in this study, using identifiers A1, A2, A3, A4, A5, and A7. The analysts worked in diverse specialist domains, including cyber threat, maritime activities, and terrorist groups. There was a single interviewer for all interviews and they used the Critical Decision Method (CDM) to explore a particular analysis task with each analyst [1] [2]. Analysts were first asked to introduce their role and a typical day, then to describe a memorable analysis task from start to end. For this study, we were most interested in capturing the processes involved throughout the analysis activity, including what the analyst did and the expertise involved. With this information we could envisage how a system could support an analyst with an appreciation of the cognition required for effective performance.

IV. Analysis

The utterances made by analysts were recorded in transcripts and analysed with a method called Emergent Themes Analysis [4] [13]. A single researcher performed the analysis to ensure consistency. They started by identifying, indexing, and collating broad themes, in terms of the processes involved in an analysis task, by mapping analyst utterances to the main aspects of the decision making path presented by Gerber et al. [3]. The analysts all described examples that involved situation recognition, intuition, leap of faith, and insight. New themes also emerged that did not clearly map to these aspects, for example, to capture the specific drivers that signalled when an analysis activity was required. For each analyst, an individual diagram was produced that showed how their utterances had been summarised and mapped to the aspects in the decision making process. For traceability the summarised diagram contained references to the original utterance data, including the identifier for the analyst and the time of the statement. Fig. 1 shows a simplified version of an individual analyst diagram. This only shows the references to utterance data for one theme (Lines of Inquiry). The others have only titles. Analysts received diagrams with utterance references for all themes. The diagram was shared with the analyst so they could verify that it accurately captured the analysis activity they had described.

The individual diagrams were overlaid and summarised, using the diagram as a visual aid to support the grouping of analysts. Each of the collated themes was given a title, summarising the statements within the theme. We drew upon existing models where possible to help with summarisation, for example, within the theme of situation recognition, we summarised statements against the Recognition-Primed Decision model [8]. The analysts identified similar core cognitive processes, despite working in different domains, at a mixture of strategic and operational levels, and performing a variety of analytical techniques. The analysts who supported each summarised statement were documented, so that the collated diagram was traceable back to the individual diagrams, and the underlying transcript data.

In this study, our focus was to understand the cognitive requirements underlying each of the processes, so that this could inform our development of HCAI that supports and respects these requirements. For each of the collated themes, a researcher sought to identify the significance of the theme, specifically, how the theme was both informed by expertise and how it informed expertise. Expertise was assumed to be a useful benchmark to identify where cognition was required where the demonstration of expertise involves more complex cognitive processes. We have tried to capture interdependencies in terms of the drivers for expertise and the requirements for expertise, within individual themes and across themes.

V. Results and Discussion

The collated diagram (Fig. 2) provides summarised titles for each of the themes, in addition to descriptions of how expertise influences the theme, and how expertise is influenced by the theme. The process is not linear, for example, at any point a new driver may emerge causing the process to repeat, or an analyst will conduct many lines of inquiry and apply a variety of different analysis techniques within the theme of 'lines of inquiry'. Themes are not associated on a one to one basis with one another i.e. many lines of inquiry may lead to a single insight, and claim may capture multiple insights. Our collated diagram captures common themes that run throughout the analysis tasks described by analysts.

Within each theme there are aspects that influence expertise and that are influenced by expertise, where interdependencies exist between themes. Here we describe each of the core themes in turn, with focus upon the role of expertise.

A. Drivers

The 'drivers' describe signals that indicated to the analysts when an analysis activity was needed. There were proactive drivers, when analysts identified intelligence gaps and looked to build capability [Analysts who described this : A3, A7], looked to predict potential future situations through horizon

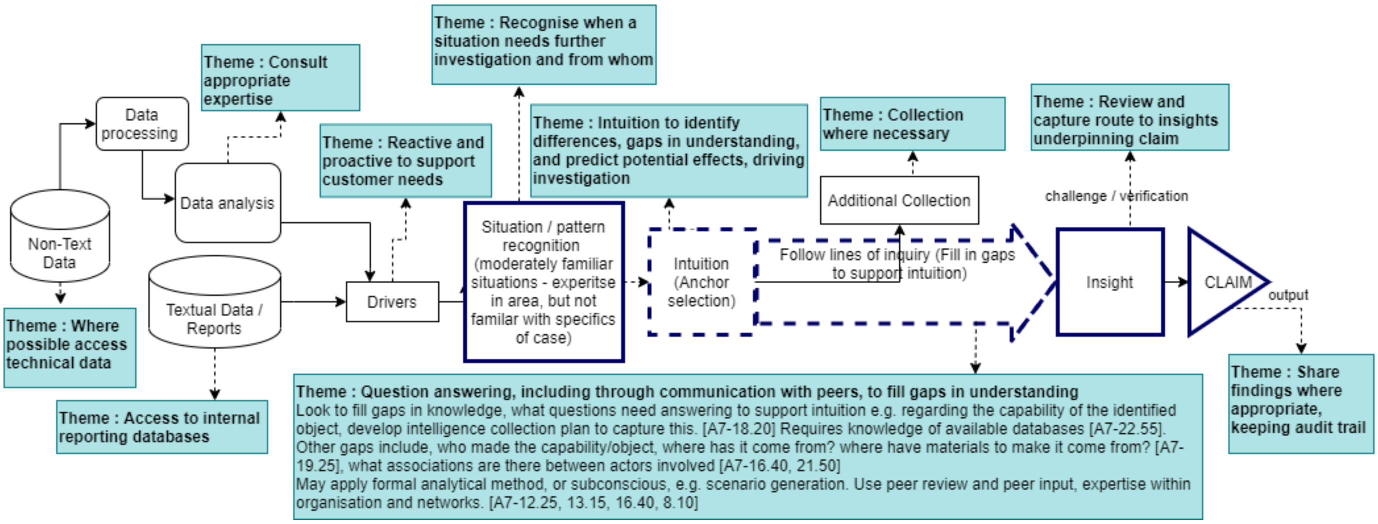

Fig. 1. Simplified example of an individual analyst diagram showing detail for ‘lines of inquiry’, with the Decision Making Path (Gerber et al. 2016) at the core.

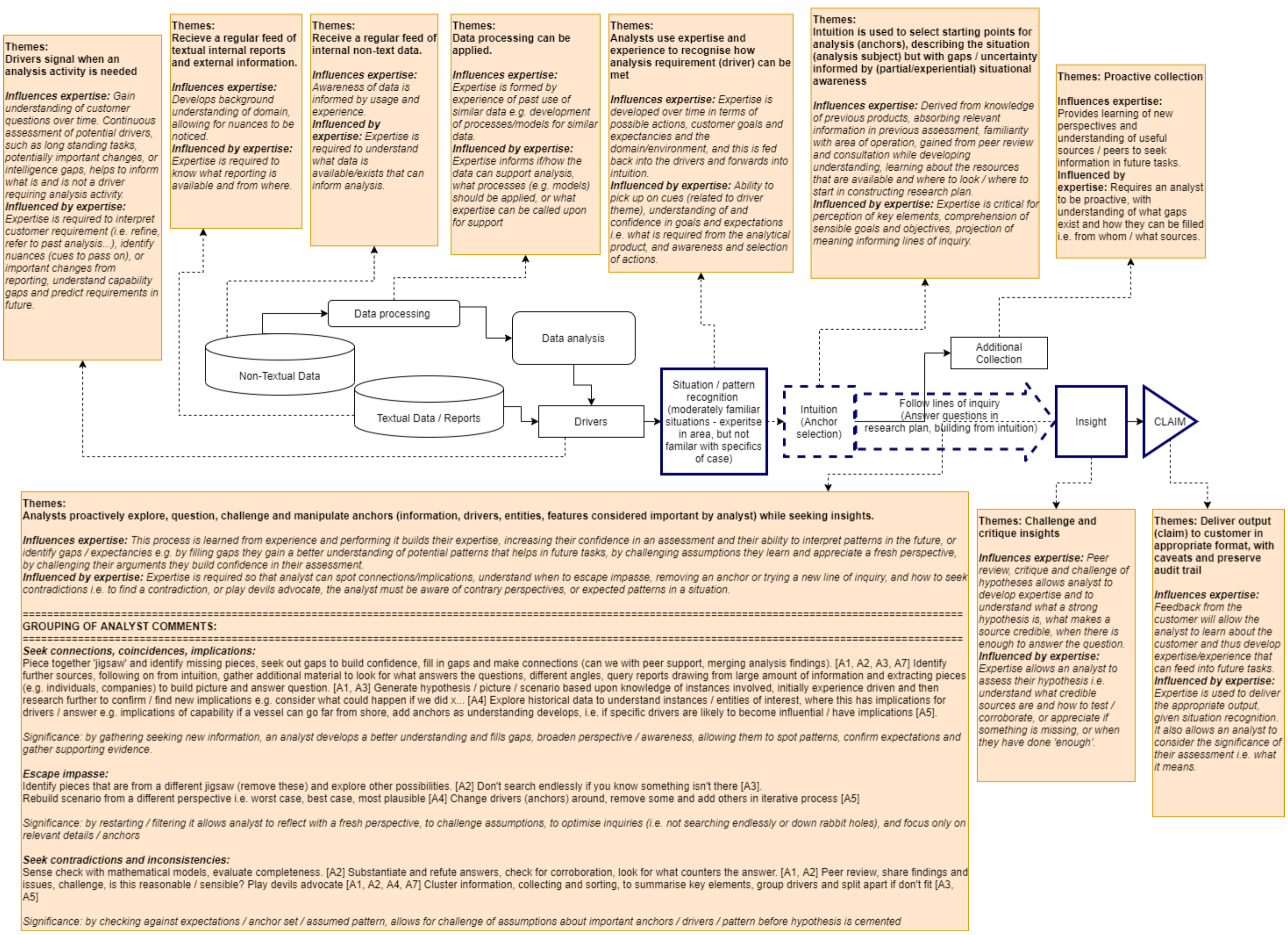

Fig. 2. Simplified collated diagram, showing detail for ‘Lines of inquiry’, with the Decision Making Path (Gerber et al. 2016) at the core.

scanning [A3, A4, A5, A7], or spotted interesting events that could be significant for a customer requirement [A2, A3, A4, A7]. There were also reactive drivers, for example, when analysts were responding to a specific question through a formal process [A2, A3, A4, A7]. Expertise was a crucial factor as it allowed the analyst to interpret or refine the requirement, identify nuances or important changes that needed further investigation, or to be aware of capability gaps and to predict future requirements. Experience of drivers helps to influence expertise, for example, over time an analyst will gain an understanding of a customer and the questions they ask. The expertise that an analyst requires to effectively identify and interpret drivers is also influenced by a background understanding of the domain and the requirement, for example, gained by reading many reports about the domain.

B. Recognition of Analysis Requirement

The Recognition-Primed Decision model [**?**] captures the key aspects described by analysts related to recognition of the analysis requirement. For example, the analysts picked up on cues such as the customer requesting the product [A1, A3, A4, A5], the specific domain and entities [A4, A5], nuances, or interesting changes against a baseline narrative [A2, A3, A7], the data involved, including an appreciation of the expertise required to interpret the data [A3, A7], and input from peers [A1, A3]. These cues were directly informed by the respective driver. Analysts formed expectations, about what the customer would find interesting [A2, A4, A5], what they would already know, what they needed, and what they would likely do with the analysis product [A3, A4]. The analysts identified possible actions to take, such as to construct a research plan and look further into a situation [A1, A2, A3, A4, A5, A7], or to seek clarification from the customer [A1], the source [A7], or peers [A1, A3, A7]. The analysts also recognised goals that would help them to address the requirement, for example, to understand the 'right' question to answer [A1, A2, A3, A4], the timescales [A1], what support and data was available [A1, A3, A7], and how the product should be delivered and what has been delivered previously i.e. format and distribution [A1, A3]. For the analysts to recognise the analysis situation effectively, they required expertise to pick up on cues, identify appropriate goals, form accurate expectations, and have an awareness of beneficial actions to take. With experience, peer support, and by refining questions with a customer, they develop expertise that allows them to understand the customer, domain, and possible actions to take in future situations. This expertise is vital, for example, without a deep understanding of the customer together with the domain, it would be difficult to form expectations about what is interesting to a customer, appropriate, or the 'right' question to research. There are important interdependencies between themes and the development of expertise when it comes to situation recognition. The drivers both influence situation recognition and are influenced by situation recognition. As analysts are involved in more situations over time this will influence how they pick up on drivers, for example, by gaining a better understanding of customer goals and expectancies, and specific domains. Situation recognition then gives a frame of reference for intuition.

C. Intuition

Once an analysis situation had been recognised, there was a need for analysts to form an appropriate awareness of the state of the environment, so they could effectively proceed with their analysis. Their awareness of the situation was partial where there were gaps, or areas of uncertainty. To fill the gaps and help guide their analysis, they used their intuition to form a narrative, or pattern, that described the environment. We can capture the key aspects where analysts used their intuition, as described by the analysts, in the Model of Situational Awareness in dynamic decision making [14]. The analysts needed to perceive important elements in the environment i.e. the key information, or details of the question [A1, A2], including important anchors, attributes, geographies, and search terms [A1, A2, A3, A4, A5, A7]. They needed to comprehend the current situation, to inform the immediate goals and objectives for their analysis i.e. they devised a research plan that would gather the information required, with an awareness of the sources of information that could be drawn upon [A1, A2, A3]. They prioritised areas to search [A3], and identified relevant expertise that could provide support [A1, A5, A7]. This would allow the analysts to plan routes for analysis. Analysts also needed to project future states and events. They needed to use their intuition to predict potential meaning, for example, why an entity was behaving how it was, what it was trying to achieve, what implications could there be [A4, A7], was it significant [A2], and what if any threats could emerge [A4]. Expertise is crucial for analysts to use their intuition. The use of intuition to derive situational awareness in turn influences expertise, where analysts learn about a domain and can better perceive key elements, more effectively form goals and objectives for their analysis through peer consultation and advice from technical experts, and acquire a firmer grasp of realistic possibilities in terms of the projection of future states from experience.

D. Follow Lines of Inquiry

Upon using their intuition to derive a partial situational awareness, analysts performed analysis activities. Various methods were applied, some formal, depending upon the requirements and the situation. In general, the analysts explored, questioned, challenged, and manipulated the 'anchors' within the initial narrative they had formed through intuition. They did so seeking insights, and we have captured the key statements made by analysts within the Triple Path model for insight [15]. Fig. 2 shows the detail within this theme, including how the summarised statements have been grouped within each aspect of the Triple Path model and the significance. Expertise is important to aid seeking insights. The performance of analytical processes also influences expertise, where the ability to do this effectively is learned from experience. When an analyst is seeking insights they may pursue avenues to collect additional information. To do this, the analyst needs to understand when a gap exists and how it can be filled. The expertise gained from proactive collection also helps an analyst to use their intuition, for example, to comprehend routes to search with an awareness of what has been useful in the past.

E. Insight

As analysts conducted their lines of inquiry, insights and hypotheses emerged. It was important that the analysts challenged and critiqued these insights before they could be used in an analytical product. The analysts described formal and informal ways to assess their confidence, the credibility, and likelihood of a hypothesis [A2, A3, A5, A7]. The role of peers to help challenge hypotheses, for example, through argument and defence was important to test if anything was missing and to understand the significance of a finding [A1, A3, A4, A5]. Expertise allowed the analysts to understand how to assess their hypotheses, for example, about what made a source credible or not, how to test and corroborate information, and when they had done 'enough' to address a requirement. The process of peer review allows for expertise to be gained where by defending a hypothesis, and associated argumentation, an analyst would learn how to recognise a strong hypothesis and the appropriate evidence. This expertise could inform how they construct research plans in the future when using intuition, and gather the appropriate evidence when following lines of inquiry.

F. Claim

The analysts provided an output, in terms of an analysis product, that articulated the claim they were making. This captured their key findings, including the significance and meaning [A2, A3, A4]. The analysts also captured their underpinning judgements and any caveats, preserving an audit trail to source reporting [A1, A3, A5, A7]. Where possible the analysts considered the impact on previous assessments and updated customers, if they felt the findings would be of interest [A2, A3, A4, A5]. Expertise, informed by the recognition of the analysis requirement, was important so that an analyst could accurately consider the level significance of their findings and envisage what they could mean. Expertise also provided an awareness of what the impact was on historical assessments, and which customers may be interested. In arriving at a claim and producing an analysis product, the analysts gained expertise on how to meet particular customer requirements, through experience of delivering a product and participation in a peer review of their product. This expertise could be fed into future tasks, particularly at the requirement recognition phase.

G. Implications

Our analysis builds upon the model for decision making paths in intelligence analysis presented by Gerber et al. [3], with a few additional details such as the influence of drivers. There are various interdependencies across themes in the model, and any particular theme should not be considered in isolation of the others. We have identified the importance of expertise throughout the analysis process, as well as the influences upon the development of expertise. We propose that this understanding can guide the design of HCAI systems. For a HCAI system to be useful, extending human perceptual, cognitive and collaborative capabilities, the system should support the use of expertise, for example, by guiding a novice analyst to make better analytical decisions. In the case of expert analysts, this support includes allowing them to interpret and challenge the underlying processes, or suggest alternatives when necessary. Expertise develops over time and a HCAI system should also be cognisant not to override opportunities for this. We would not want a novice analyst to remain a novice indefinitely.

One theme that influences an analyst's expertise is where they regularly monitor information fed through to them, for example, by reading text reports. By reading these reports an analyst gains a deep understanding of the domain, which gives them a frame of reference to spot nuances, such as things that are unusual or unexpected. This expertise influences their ability to spot drivers, to recognise the requirements of an analytical task, to perceive the key elements of the situation and project their meaning, and to explore lines of inquiry. Essentially, the expertise they develop by reading reports and learning about a domain is crucial throughout the entire analytical decision making path. If an automated process was introduced that could extract entities from textual reports and populate a database, no longer requiring the analyst to read the reports themselves, it may on the face of it appear to be a useful way to reduce analyst burden. However, by not reading the reports and developing domain expertise, an analyst would be less able to spot new drivers for analytical tasks that rely on a baseline awareness of what normal looks like. There would also be an impact on downstream analytical and cognitive processes, for example, how they identify information that the customer will be interested in, priorities for investigation, contextual nuances, missing information, and irrelevant information. An automated entity extraction system would need to ensure that expertise could still be gained, for example, through use of visual aids that present the data in a way that an analyst can still develop background understanding and expectations about the domain.

Blind automation of processes within the analysis decision making path can be damaging, whereas, if designed from a human-centered perspective, a system can both support an analyst to use their expertise and to develop their expertise. For example, there are many ways that AI systems could support analysts to explore, question, challenge, and manipulate anchors or hypotheses, while seeking insights. A system could be used to spot patterns and connections, draw out different perspectives and possible hypotheses to help an analyst escape impasse, or look for contradictions and inconsistencies that challenge a hypothesis through argumentation. However, analysis tasks are entwined with uncertainty where much of the information required is missing, and there are gaps in knowledge and collected data. This is a problem in the case of AI systems that cannot manage when data is lacking, or assume all the data has been gathered. There are cases when additional data collection to fill gaps could open valuable paths for analysis. If a system simply provides a result to an analyst, without transparency of the reasoning involved, then the analyst cannot use their expertise effectively, for example, to form an understanding of potential patterns of interest, lines of inquiry that have been explored, and lines that could be augmented, or the nature of arguments used. Nor can they learn from the system or develop expertise that would be useful in future analysis tasks. A lack of transparency may also harm other themes of the analysis decision making path, for example, using intuition to construct a research plan or performing proactive collection. A HCAI system would provide the appropriate level of transparency for an analyst to interpret the behaviour of the system and develop expertise.

H. Conclusion and Future work

Our interview study has explored the role of expertise across analyst decision making paths. Expertise is crucial in the domain of intelligence analysis, where drivers, requirements, and situations are complex and interdependent. There is a lot of potential for AI systems to support analysts throughout an analysis task, by enhancing their expertise with an understanding of how expertise is used. However, systems must also support the context that helps develop expertise. We propose that this requires HCAI, that reflects the human context in the design of the system. In this paper, we describe the human context in terms of expertise and our findings can therefore help the design of HCAI. In future work, we will explore how HCAI systems can be designed and developed, applying our findings.

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REFERENCES

[1] G. A. Klein, R. Calderwood, and D. MacGregor, "Critical decision method for eliciting knowledge," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 19, no. 3, pp. 462–472, 1989.

[2] W. B. L. Wong, *Critical Decision Method Data Analysis*. Lawrence Erlbaun Associates, 1993, pp. 327–346.

[3] M. Gerber, B. W. Wong, and N. Kodagoda, "How analysts think: Intuition, leap of faith and insight," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, no. 1, pp. 173–177, 2016. [Online]. Available: https://doi.org/10.1177/1541931213601039

[4] W. Wong and A. Blandford, "Analysing ambulance dispatcher decision making: trialing emergent themes analysis." *Vetere, F and Johnson, L and Kushinsky, R, (eds.) Ergonomics Society of Australia: Canberra, Australia.*, 2002.

[5] "National intelligence machinery." [Online]. Available: https://www.gov.uk/government/publications/national-intelligence-machinery

[6] B. W. Wong and N. Kodagoda, "How analysts think: Inference making strategies," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, no. 1, pp. 269–273, 2015. [Online]. Available: https://doi.org/10.1177/1541931215591055

[7] G. Tecuci, D. Schum, M. Boicu, D. Marcu, and B. Hamilton, "Intelligence analysis as agent-assisted discovery of evidence, hypotheses and arguments," in *Advances in Intelligent Decision Technologies*, G. Phillips-Wren, L. C. Jain, K. Nakamatsu, and R. J. Howlett, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 1–10.

[8] G. Klein, *A recognition-primed decision (RPD) model of rapid decision making.* Abex Publishing, 1993, pp. 138–147.

[9] J. Rasmussen, "Taxonomy for cognitive work analysis."

[10] D. Leslie, "Understanding artificial intelligence ethics and safety: A guide for the responsible design and implementation of ai systems in the public sector." 2019. [Online]. Available: https://doi.org/10.5281/zenodo.3240529

[11] S. Hepenstal, N. Kodagoda, L. Zhang, P. Paudyal, and B. L. W. Wong, "Algorithmic transparency of conversational agents," in *Joint Proceedings of the ACM IUI 2019 Workshops co-located with the 24th ACM Conference on Intelligent User Interfaces (ACM IUI 2019), Los Angeles, USA, March 20, 2019*, ser. CEUR Workshop Proceedings, C. Trattner, D. Parra, and N. Riche, Eds., vol. 2327. CEUR-WS.org, 2019. [Online]. Available: http://ceur-ws.org/Vol-2327/IUI19WS-IUIATEC-1.pdf

[12] W. Xu, "Toward human-centered ai: A perspective from human-computer interaction," *Interactions*, vol. 26, no. 4, p. 42–46, Jun. 2019. [Online]. Available: https://doi.org/10.1145/3328485

[13] B. W. Wong and A. Blandford, "Describing situation awareness at an emergency medical dispatch centre," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 48. SAGE Publications Sage CA: Los Angeles, CA, 2004, pp. 285–289.

[14] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *Human Factors*, vol. 37, no. 1, pp. 32–64, 1995. [Online]. Available: https://doi.org/10.1518/001872095779049543

[15] G. Klein, *Seeing what others don't. The Remarkable Ways We Gain Insights.* Nicholas Brealey Publishing, 2017.