Learning from Expert Teams

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SUMMARY

We studied the experimental adoption of an image classifying tool as an organisation plans the adoption within its teams of intelligence analysts. We identified that existing models of expert decision-making and function allocation can be employed to inform the design and adoption of these tools.

KEYWORDS

Trust, allocation, decision-making, interdependence

Introduction

Expert Defence Intelligence analysts study large volumes of data under conditions of uncertainty; using the acquired domain knowledge, they apply critical thinking to make decisions and predictions. Advances in Artificial Intelligence (AI), including machine learning algorithms and robotics as a component of automated decision making, are predicted to provide many benefits to the analysts' decision-making task (Hoffman et al., 2018). Many challenges could prevent the adoption of such tools in an organisation, from integration into the organisation's information systems to Human-Automation trust issues (Hoff and Bashir, 2015). We study the adoption of an image classifier as a case study of automated decision-making tools in an organisation. The image classifier tool can detect, recognise and track objects, providing a percentage certainty for those objects that it identifies. The tool is expected to increase productivity, reduce the time taken for analysis, and increase decision-making accuracy. This study builds on existing research that has called for human-automation interaction (HAI) to keep pace with the adoption of automated tools at an individual level (Burns, 2018) and extend it to the expert team setting, by questioning what is informing analysts' trust within an expert team setting.

Method

We interviewed four teams of three analysts prior to and after the deployment of the image classifying tool within an experimental setting. Interview questions were constructed using current research on the relationship team members perceived to have with the tool (Hoffman & Johnson, 2019; Jennings et al., 2014), on what was informing their trust (Hoff & Bashir, 2015), how the tool would support their decision making (Klein, et al., 1993) and the functional allocation between the tool and analysts (Cummings, 2018). Data analysis was conducted using Bruan's six-phase guide (Braun & Clarke, 2019) to identify codes and emergent themes within the data, to form the basis of our qualitative analysis.

Initial Findings

Themes that emerged when analysts described their relationship with the tool:

A. Relationship: Six of twelve analysts described it as purely a tool and something which they might find themselves supervising.
B. Relationship: Three of twelve analysts noted that the tool was part of their internal dialogue as they identified objects, informing what was occurring within the scene.
C. Interdependence: Nine of twelve analysts identified that there was an *Interdependence* between the analysts and the tool, supporting the Hoffman & Johnson (2019) proposal of an emerging interdependence between users and automation.
D. Interdependence: Five of twelve analysts described a varying degree of *Interdependence* between themselves and the tool.
E. Interdependence: Four of twelve analysts identified that the degree of *Interdependence* varied depending on the criticality of that which was being undertaken, adapting the roles and levels of trust allocated to the tool.

Themes that emerged when the analyst described how they perceived the tool might support their recognition primed decision-making:

F. Decision Making: Nine of twelve analysts stated that the tool supported them through the provision of cues, thereby informing their situational awareness.
G. Decision Making: Six of twelve analysts described that the automated tool helped inform their expectancy around what it was that they were observing.
H. Decision Making: Two of twelve analysts described that the tool informed the actions they may take, or the plausible goals that could be achieved.

Conclusion

Kamkar's description of object detection, recognition, object tracking, activity and scene recognition (Kamkar et al., 2020) provides a method to describe the analysts' activity as they make a prediction of activity and scene recognition. Our intial findings are that *Interdependence* between the analysts and tool can be described using two existing models, that of the recognition primed decision making (Klein, et al., 1993) and the role allocation for information processing model (Cummings, 2018), which, when modified using Kamkar's functions of object detection and recognition and object tracking (Kamkar et al., 2020), provides a view of the tool and analyst *Interdependence.* While Cummings' model describes uncertainty, it does not recognise the criticality of the situation which four of twelve analysts stated would adapt the role and trust in the tool; this should be investigated in the further research. At an individual level, the recognition primed decision-making model provided a framework for understanding where the tool was supporting the analysts' judgment. Our intial findings identify the tool provided them with relevant cues, additional recognitions within the scenes for their judgment. The tool informed their expectancies, required to check the accuracy of the situational assessment they have made. Our intial findings indicate that Klein's model provides a framework to identify where these tools support analyst decision-making. Further investigation would be required to identify how Klein's model could be used to inform appropriate design and employment of image classifiers within expert analyst teams.

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