Human-AI Cooperation to Benefit Military Decision Making

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ABSTRACT

Military decision making takes place in variety of complex domains (defense, security, cyber, etc.). Artificial Intelligence not only allows for data reduction and synthesis, but also for the development of predictions about future events, and about outcomes to considered interventions. However, due to the often uncertain circumstances and ill-defined problems, AI cannot yet do this autonomously. Instead, deriving decisions from predictions and analysed data should be organized as an interactive human-technology activity, in which both parties become aware of one another's strengths, limitations, and objectives. This paper addresses how humans and AI-systems should cooperate to achieve better decision making. It is argued that situation judgment can be improved through interactive explanatory dialogues, and that well-chosen explanations will support judgments and goal setting. An AI-system should be able to adapt itself dynamically to the decision maker, by taking into account his objectives, preferences, and track record (e.g. susceptibility to bias). Furthermore, this approach also contributes to 'trust-calibration': a level of warranted trust in each other's competencies. It is proposed to discern different stages in human-AI collaboration, ranging from one-way messaging to actual teaming. Ideally, AI-systems should be able to function as intelligent team players, but also at lower levels of collaboration, human-machine performance can be substantially boosted.

1. INTRODUCTION

Military decision makers are often faced with complex problems in non-routine situations for which no automated or rule-based solutions exist. The decision makers and their teams have to collect, analyse and synthesize information to build an understanding of what is happening; they have to subsequently develop options for action and consider the consequences of different courses of action. Military missions are regularlyn staged in regional conflicts, and more often than not, there is uncertainty about the intentions, capabilities and strategies of the parties involved.

Military decisions need to be made based on up-to-date, relevant and timely information (Louvieris, Gregoriades, & Garn, 2010). Thanks to the recent growth in sensor technology and analysis software, the military generally has systems available that provide large streams of information related to a decision situation. However, information becomes burdensome if supplied in large quantities and in an uncontrolled manner. It may increase the decision maker's workload due to the need to process all this information. The resulting 'information clutter' thus endangers situation awareness and the quality of human decision making. Given this, the need for decision support systems that fuse, process, and interpret information is evident.

Traditionally, humans and automated systems have fulfilled complementary but separated functions within military decision making (Hosack, Hall, Paradice, & Courtney, 2012). However, recent advances in information technology and in artificial intelligence (AI) allow for a more coordinated, and possibly more integrated functioning of humans and technology. This paper presents a view on the positioning and role of artificial intelligence in decision support systems. The claim is that in truly intelligent decision making systems, humans and technology work collaboratively, with a shared understanding of the task, the context, and each other's perspectives and capabilities. It is argued that current decision support systems do not yet have these qualities, and that the field requires several stages of progress to achieve the desired level of human-AI collaboration in decision making.

2. HUMAN DECISION MAKING

Soldiers, like all people, constantly make decisions. This may involve routine as well as unexpected, challenging situations. Human judgment and decision making is the result of a complex interplay of many simultaneous factors, such as sensations, feelings, memory, emotions, and thoughts. In reality, these interlinked processes develop in a jumbled and mingled fashion in the brain (Harari, 2016, p.123), but theories generally distinguish between two distinctive types of thinking (Evans, 2008). The first type (Type 1) is generally intuitive and automatic, sub-conscious, associative, affective and heuristic-based. A heuristic is basically a rule of thumb that provides a solution of a complex problem by simplification. When a person is faced with a difficult question or situation that is hard to solve, his mind reformulates the problem into a related problem to which an answer comes easily available. This reshaping of the problem occurs subconsciously, without the person being aware of it. The second type (Type 2) entails deliberate and controlled processes, and is slow, effortful, conscious, and rule-based. Humans make many or most of their decisions intuitively and unconsciously, in a blink of an eye (Gladwell, 2007; Kahneman, 2011). While intuitive decision making may be very effective and efficient (Dane, Rockmann, & Pratt, 2012), relying on intuition may also lead to bias and erroneous judgments and decisions. A biased judgment or decision systematically deviates from logic or from utility. In some situations, biases can have serious consequences, especially when stakes are high, as is often the case in military operations.

Williams (Williams, 2010) discusses how the application of heuristics may lead military judgment and decision making astray. One example is that an officer who has witnessed one or more IED-attacks is likely to overestimate the likelihood of future attacks. The impact and salience of the experienced incidents make the attacks highly available in the officer's brain, leading to a distorted subjective probability assessment. The availability heuristic (Slovic, Fischhoff, & Lichtenstein, 1980) causes the officer to subconsciously reformulate the hard-to-answer problem "how likely is an IED on this route?" into a more easy to answer problem "how vividly can I imagine an IED attack along this route?". Williams blames well-known military disasters, such as the Bay of Pigs fiasco and the Vietnam War, to the fundamental limitations of human judgment and decision making.

Another factor that makes human decision making hard is uncertainty. And uncertainty is what typically characterizes military situations. Modern military missions take place in dynamic and highly interactive contexts, carrying new threats (Paparone & Reed, 2011). Assessing a tactical situation usually requires considering a large number of variables (e.g., strength of own forces, estimated force and intentions of enemy, weather- and terrain conditions, behaviour of the population, communications, et cetera), of which the status is often not known or uncertain. In fact, military conflicts are characterized by so-called 'deep uncertainty' (Jong, Daalen, & Dekkers, 2014). Yet it is the responsibility of the military commander to understand the conflict, and to generate and deploy the resources to control it, taking the mission orders and constraints into account. To deal with uncertainty, a commander must make assumptions and inferences. The problem with making assumptions and inferences is that there soon are too many of them, and that their relationships cannot be assessed. It yields a combinatorial explosion that can no longer be managed by human analysis and reasoning.

A problem of a more psychological nature is that humans find it difficult to accept uncertainty, and thus try to dismiss or ignore it whenever possible (Kahneman, 2011). We are prone to overestimate how much we understand about the world (overconfidence bias) and to underestimate the role of chance in events (the illusion of certainty). An analytical approach to evaluating a military tactical situation requires an unbiased appreciation of its uncertainty - but that is not what people and organizations do and seek. Accepting uncertainty can be paralyzing, especially under dangerous circumstances, and the admission that one is merely guessing is especially unacceptable when the stakes are high. Acting on pretended knowledge is often the preferred solution, which may lead people to take risks that they would not if they knew the odds.

3. MILITARY DECISION MAKING

The military consider decision making as a continuous and cyclic process, as it is constantly fed by new and updated information from the environment. In order to create structure and unity, the military forces have developed dedicated methods for conducting their decision making processes (e.g. the NATO Allied Doctrine for Operational Planning). Every commander at every level[1] goes through such a decision making process. However, depending on the level of the commander, and the complexity of the environment and assignment, the process is more extensive and complicated. What the methods on all levels have in common is that they employ formalized and standardized analysis and procedures.

The methods for decision making reflect the military's analytical approach to problem solving. They assist commanders and staff to examine a situation and to reach logical decisions. It helps them to apply thoroughness, clarity, sound judgment, logic, and professional knowledge to reach a decision. The full decision making process is detailed, deliberate, sequential, and time-consuming, especially when adequate planning time and sufficient staff support are available to thoroughly examine various friendly and enemy courses of action (COAs). The advantage of the approach are that:

- it analyses and compares multiple friendly and enemy COAs in an attempt to identify the best possible friendly COA;
- it produces the greatest integration, coordination, and synchronization for an operation and minimizes the risk of overlooking a critical aspect of the operation;
- it results in a detailed operation order or operation plan.

The analytical approach, however, has several disadvantages. For one, it may give the decision maker a false sense of covering a problem completely and systematically. As argued above in the previous section, Kahneman and others (e.g., Kahneman, 2011) have demonstrated that even when people intend to evaluate a situation systematically according to a structured approach, they are often unable to do so, without even being aware of that themselves. Their analysis is often impaired by tendencies to neglect information, to interpret information wrongly, and to make incorrect argumentations. A second drawback is that the classic military process of decision making is time and manpower consuming (Paparone, 2001) and is dramatically limiting the number and diversity of options able to explore and analyse (Banner, 1997).

These circumstances make it necessary to develop and employ systems that support the decision making of military commanders for the following reasons:

- the vulnerabilities of human decision making,
- the diversity and complexity of conflict situations,
- the information and technology means employed in warfare,
- the amount of information needed to be processed in real time.

[1] Ranging from the platoon commander to a division commander, to a commander at a strategic headquarters

4. INTELLIGENT DECISION SUPPORT SYSTEMS

4.1 Properties of (Intelligent) Decision Support Systems

The need for systems with the purpose to assist humans in their decision making stems back from the days of Herbert Simon, who argued that people may be rational but are limited in their cognitive processing abilities when they have to deal with complex problems. He referred to this as 'bounded rationality' (Simon, 1972). Simon argued that bounded rationality brings human to accept solutions that may not be optimal, but are 'good enough'. Simon coined the term 'satisficing' for the latter mechanism. The desire to overcome these fundamental limitations of humans has resulted in the development of Decision Support Systems (DSSs).

A DSS can be characterized as a model-based set of procedures for processing data and judgments to assist decision makers to solve semi-structured and unstructured decision tasks. In addition, a DSS stimulates the decision maker to follow the prescribed decision making process and helps to make the right decision (Susnea, 2012). An *intelligent* decision support system (IDSS) is a decision support system that makes use of artificial intelligence (AI) techniques (Kaklauskas, 2015). An IDSS may support decision makers by collecting and analysing evidence, detecting familiar patterns in the data, checking hypotheses, suggesting possible courses of action, and evaluating the appropriateness of proposed actions.

IDSS implementations typically combine knowledge of a particular application domain (e.g., military tactics) with an inference capability to enable the system to propose decisions or diagnoses. Accuracy and consistency can be comparable to (or even exceed) that of human experts when the decision parameters are well known but performance will generally be poor when novel or uncertain circumstances arise.

IDSSs can respond to new and uncertain situations by the use of specialized functions (e.g. intelligent agents) that perform cognitive tasks related to decision making, such as knowledge representation, intent recognition, machine learning, automated inference, and data mining. These AI-techniques can be classified into Expert Systems, Bayesian Belief Networks, Fuzzy Logic, and Neural Networks (Moisescu, Boscoianu, Prelipcean, & Lupan, 2010).

IDSSs should, in principle, be helpful to the military to make better decisions by discovering familiarity in patterns of events that might otherwise pass unnoticed to the human decision maker. When evaluating an optional course of action, an IDSS can take many more variables into account than humans can, thereby achieving a better and more refined prediction of outcomes. An IDSS may also be helpful in the decision making process by being alert to possible cognitive biases of the human decision maker. It may, for example, be more neutral and accurate than a human when judging whether a proposed action complies to the rules of engagement. Finally, an IDSS may, by virtue of its analysing capabilities, be able to speed up the process of sense making and situation understanding.

Intelligent Systems, thus, could aid the decision making process in several ways. The following attributes represent successful systems (Guerlain, Brown, & Mastrangelo, 2000):

A. *Interactivity*: the system works with the human user(s) to explore the 'space of possibilities' in a constraint-based way, instead of just providing the one 'optimal' solution.
B. *Event and Change Detection*: the system recognizes and effectively communicates important changes and events.
C. *Representation aiding*: the system represents and communicates information in a compelling, informative, and human-centered way (e.g., by smart visualization, or 'dashboarding').
D. *Error Detection and Recovery*: the system checks for typical reasoning errors made by people (e.g. bias). Further, the system has knowledge of its own limitations and checks for situations for which it may not be as fully capable.
E. *Information out of Data*: the system uses intelligent algorithmic techniques to infer and generate

information from the available data.

F. *Predictive Capabilities*: The system can predict the effect of actions on future performance (*what-if* analyses).

In addition, an intelligent decision support system may assist *Risk Analyses* (Prelipcean & Boscoianu, 2011).

4.2 Shortcomings of (Intelligent) Decision Support Systems

Whereas (I)DSSs can ideally act as powerful aid for human decision making, the current state of the art is hampered by a number of shortcomings, which limits their reliability and applicability.

a. *Emphasis on technology*: There is a strong emphasis on technology, for example for improving data fusion and classification performance. However, as Hosack and colleagues argue, progress needs better awareness of the pervasiveness of technology, and understanding of how to design processes that use the capabilities of technology such that organizational outcomes are enhanced (Hosack et al., 2012, p.326). In other words, the focus should not only be on technology but also on ways to make it work in a (defense) organization.

b. *Emphasis on modelling the world, little emphasis on modelling the user*. The development of models for (I)DSSs concentrate on modelling the world. Much less attention is given to modelling the human decision maker. However, adequately modeling the user may enable the DSS to engage in a smoother and more coordinated cooperation with the user. In addition, such models may allow a system to be alert to possible systematic errors and bias on the part of the user, and may provide alerts timely and proportionally.

c. *Insufficient trust*: A problem in the design of any decision aid is how to design it so that the decision maker will trust it, and therefore use it appropriately (Hoff & Bashir, 2015). Just as it does in human-human relationships, trust determines the willingness of humans to accept the outcomes of automated systems in situations that are characterized by uncertainty. Facilitating higher levels of appropriate trust in IDSSs is important to improve their effectiveness and use.

d. *Model incomprehensibility*: Recent advances in Artificial Intelligence in combination with rapidly increasing computer power have unlocked new methods of modelling complex environments and uncertainty. Big Data tools have become important for collecting massive amounts of domain-specific information; Deep Learning algorithms extract high-level, complex abstractions from these data (Najafabadi et al., 2015). These models undeniably have enormous potential for the support of military decision making. However, because they currently provide no information on how results are obtained, they are a black box in the eyes of a human user, hampering the user's trust in the model and the system.

e. *Model scope and model rigidity*. A characteristic of AI tools such as neural networks is that they have been trained for a very specific task, where they can perform well, sometimes at super-human levels (Silver et al., 2016). Yet if the context of application changes (as is to be expected in military contexts), the accuracy may drop considerably because the AI is generally unable to adapt (Horowitz, 2018; Lake, Ullman, Tenenbaum, & Gershman, 2017).

f. *Model vulnerability*. AI tools can be unexpectedly vulnerable to adversarial attacks. Image classifiers can, for example, be induced to generate completely erroneous results by adding a specific patch or (invisible) noise pattern to an image (Brown et al., 2017). Due to model incomprehensibility, such errors may well pass unnoticed, compromising the reliability of the entire DSS.

An overall feature characterizing many drawbacks of (I)DSSs is that the intelligence in the system and the human user do not form a unity, but that both more or less operate separately. The intelligence is often no more than an *add-on* to the human decision maker.

5. TOWARDS INTELLIGENT HUMAN-AI COLLABORATED DECISION MAKING

5.1 Requirements of human-AI collaborated decision making

There is a growing awareness that intelligent decision support should not be presented to the human decision maker as a distinct system, or as a working tool. Rather than being separate entities, human and machine should collaborate. Decision making should be considered as a joint activity of humans and intelligent technology, working together in a collaborative and coordinated fashion. Klein and colleagues (Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004) argued that successful joint activity demands the following requirements of partners:

- be mutually predictable in their actions
- be mutually directable
- maintain common ground

If the partner of a human decision maker is an IDSS, then the AI of the support system needs to be 'human aware'. This ideally includes awareness of human tendencies in general (e.g., proneness to bias), but also of characteristics of specific team members (e.g., current work load; preferences, prior knowledge; emotional state; competencies; history of making biased judgments; et cetera). In addition, the AI should have knowledge of the context within which decisions have to be made and of its role within that process. This enables the AI to, for example, accept and delegate tasks and responsibilities, taking into account the possible constraints. Furthermore, it also enables the AI to make sense of dynamic adjustments in work-agreements issued by the human; it may itself propose or even proclaim such adjustments, or to draw in expertise from outside the human-AI dyad.

Johnson and colleagues (Johnson et al., 2014) argue that in human-robot teams it is important that team members work in an interdependent fashion, where interdependency is taken as 'actively managing dependencies in joint activity'. A human-robot team is designed to support interdependence if it meets the requirements of observability, predictability, and directability. *Observability* implies that each team member is aware of the status of all team members, the team as a whole, the task, and the environment. *Predictability* means that actions of a team member are – to some extent – predictable, so that team members can anticipate to it. *Directability* refers to the property that team members are able to take over and delegate tasks among each other, both reactively and pro-actively. We think that the requirements of observability, predictability, and directability are equally valid when incorporating AI and IDSS in (military) decision making.

5.2 Developing mutual awareness in human-AI decision making teams

This reciprocity in the properties of a co-active decision making system implies that not only the AI should be 'human aware'; humans should be 'AI-aware' as well. The human should develop, and eventually have, a proper understanding of the contributions that the AI-partner can deliver, and which not. Becoming an 'AI-aware' human user is not self-evident; it will be difficult for people to understand the AI's language or inner workings, or to state their needs in a form or language that the AI can understand.

Humans and AI will generally not have mutual understanding of each other right from the start. Instead, this needs to develop along the way, through interaction during training and operations. Of course, the human should be instructed and trained to be receptive for understanding an AI-system, and the AI should be equipped with the functionalities required to develop an awareness of his human team-mate. In addition, the human may decide to feed the AI with some personal data. But the real understanding and the mutual awareness itself develops over time, through interaction, experiences, and feedback from the environment and from the team members (see Figure 1).

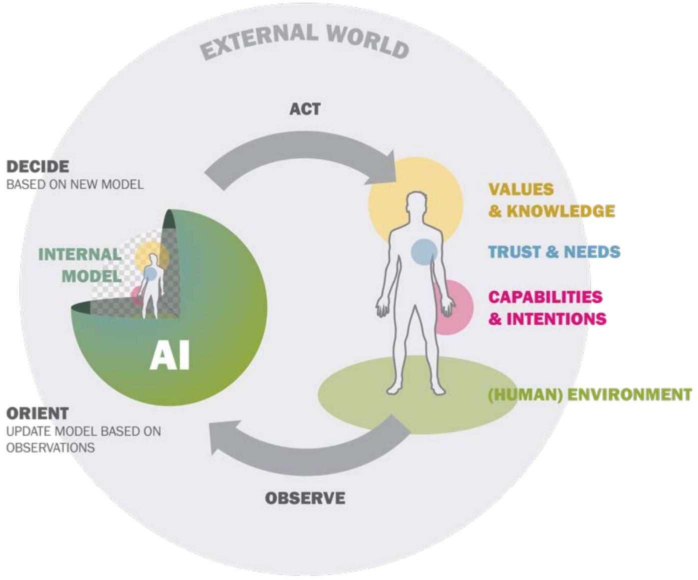

Figure 1: Human and AI jointly developing mutual awareness through interactive collaboration

In our view, the AI and the human jointly and iteratively refine their conceptualizations of each other's behavior. Therefore, the AI should be endowed with an internal model of its human collaborator, comprising knowledge as well as values, needs, intentions, and capabilities. This internal model is partially provided by human factors theories and by specific knowledge of the decision making domain. It (hopefully) suffices to initiate collaboration. But then both parties develop as a result of their interaction. Their internal models are being updated with new observations and through interactions with the external world. The growing models allow for better judgment and better reasoning about the effects of possible actions in the outside world.

When humans constitute a team (human-human teams), they sometimes fail to understand each other, even when they are skilled. Humans are generally quite capable to diagnose the cause of the misunderstanding, and to provide an explanation that restores the mutual understanding. Such misunderstandings and misalignments will also occur in human-AI teams. And like in human teams, both members need to be able to diagnose the cause, and to generate an explanation that gets the system as whole back on track (de Graaf & Malle, 2017; Miller, 2017). However, this will be quite a challenge. For example, AI-models based on current machine learning techniques offer almost no clues to humans as to how they actually work. Recently there have been attempts to develop techniques that can provide more insight (e.g., Garcez et al., 2015; Lake et al., 2017), but this problem is far from being solved.

5.3 Steps towards Human-AI decision making: levels of human-AI collaboration

The vision of mutually aware human-AI decision making is still far away. How can we move towards this goal starting from the present situation, with AI that is largely unaware of humans and their goals, values, needs, and intentions? As illustrated in Figure 2, we differentiate six levels of human-machine collaboration, where the first four levels are characterized by the type of human-AI interaction, and the last two levels by the type of human-AI collaboration. It is important to note that the levels can also be seen as modes of a collaborative system, which can switch between them depending on the teaming requirements.

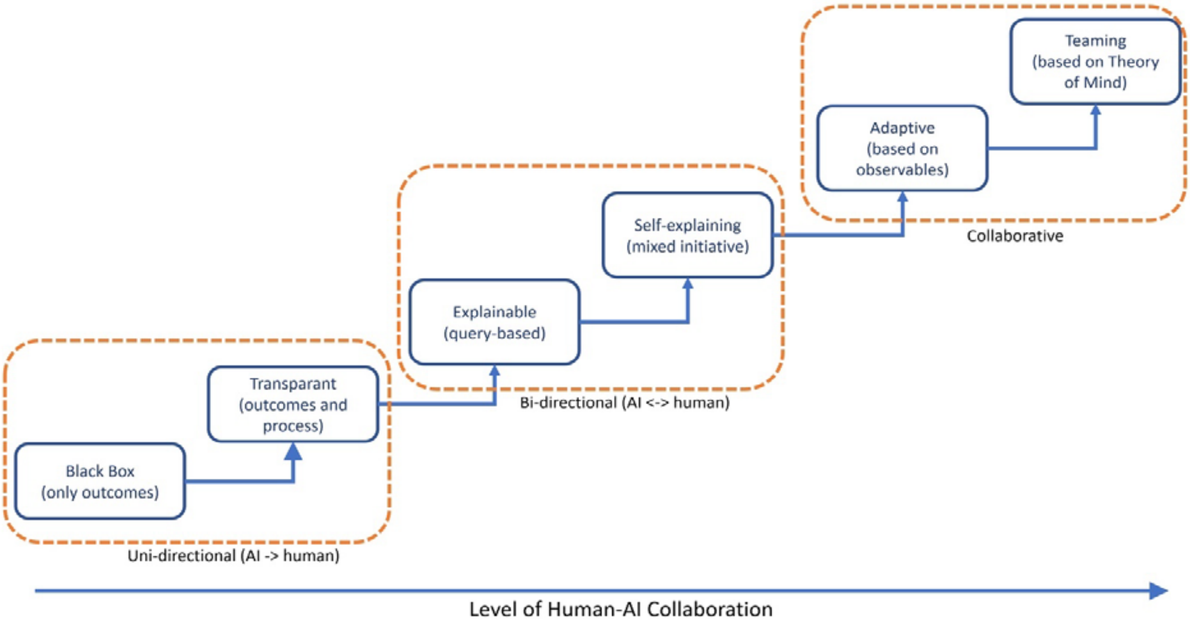

Figure 2: Levels of human-AI collaborative decision making

The first developmental step, in our view, takes place in the stage where interaction between humans and AI is still *uni-directional*. This means that progress can be achieved by improving the functionalities within the AI-partner of the system. The current situation is that any contributions from AI is largely still a black box in the eyes of the human user. What is needed are functionalities that reveal the workings of AI, so that the user understands how an outcome of the AI-system has been produced. In other words, the AI will then have become more *transparent* to the user (Theodorou, Wortham, & Bryson, 2016).

The next developmental steps will involve *bi-directional* interaction. This requires functionalities that enable the human to acquire a better understanding of the AI. One way of achieving this is by requesting explanations from the AI on demand. The initiative for clarification then lies on the part of the human, and requires from the AI the capability to determine the purpose of the human's request, and to select and generate a (set of) explanations that fit the purpose (*query-based explanations*). A more elaborated functionality is when 'explanations' can be initiated by either party (*mixed-initiative*). In this stage it is not only the human that can express a need for information, but also the AI that can voluntarily provide information, for example when it detects misunderstandings, possible errors of judgment (e.g., bias), or unjust exclusions of COAs during planning. For this, the AI should have functionalities to diagnose such states and provide analyses and arguments that are comprehensible to the human.

In the next development step, humans and AI will form a truly collaborative unity in decision making. They are full-fledged adaptive team members, being aware of each other's perspective and states (Parasuraman, Barnes, Cosenzo, & Mulgund, 2007). During overload or emergencies, humans and AI cooperatively redistribute tasks (*adaptive collaboration*) (Barnes, Chen, & Hill, 2017). In this stage, collaboration builds upon the pre-created concepts and models, but humans and AI's alike strengthen their understanding of each other by harvesting the feedback and information released during their interaction.

Ultimately they form elaborated representations of their partner's mental state (Lemaignan, Warnier, Sisbot, Clodic, & Alami, 2017). With the capabilities to form *Theories of Mind* humans and AI have developed the capability to maintain common ground, thereby meeting the challenge of Klein and colleagues (Klein et al., 2004) for successful joint activity.

6. CONCLUSION

Military decision making can benefit tremendously from advances in AI and Big Data analytics. In fact, the immense proliferation of data from sensors, media and intelligence *requires* that fusion and interpretation of incoming information will in the future be done largely automatically. Fortunately, AI tooling (e.g. for deep learning and reasoning) is becoming extremely sophisticated, opening the way for powerful IDSSs. However, we must not forget the lessons that Expert Systems and other early DSSs have taught us. In addition, while we certainly should exploit the power of these new tools, we must also be aware of their limitations. In this paper, we propose that the best way to harness and utilize AI for (military) decision making is to strive towards effective human-AI collaboration. The AI should eventually function (and be seen) as a team player that is adaptive, communicative and aware of the context and goals of the team and its members. Then, it can optimally support the team while there will also be safeguards against malfunctions and errors.

Currently, most AI-based systems are black boxes that present outcomes without suitable substantiation. Efforts are now directed at increasing the explainability of systems, which should lead to more insight into factors underlying the outcomes. While this will be a major step forward, we argue that explainable AI only represents the lowest level of ‘bi-directional’ human-AI collaboration. To reach the next higher level, the AI should also initiate interactions, which means that it should be able to detect conditions where this is necessary. At the highest levels, the AI should be capable of perceiving and reasoning about actions and intentions of human team members, so that it can act in an adaptive, intelligent manner. Pushing AI towards higher levels of human-AI collaboration will also lead to better trust calibration. While trust is an important requirement in the use of AI-based systems, it is also a problematic concept because, while it should ideally match system reliability, it is in practice dynamic and dependent on contextual and individual factors (Lee & See, 2004). In addition, when a system shows adaptive behavior, trust should evolve with it. Human-AI collaboration facilitates the dynamic process of trust calibration because it allows the human to continuously experience, interrogate, and judge the functioning of the AI.

While this paper presents a view grounded in human factors research, the stepwise approach we advocate aims to link this with progress made within areas such as AI and Information Technology. It is clear that progress in development of (I)DSSs can only be achieved in a truly multidisciplinary effort, involving not only scientists with different fields of expertise, but also technology developers and domain experts.

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