Roles of AI and Simulation for Military Decision Making

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ABSTRACT

Military decision making plays a key role across different domains – land, maritime, air, space, and cyber – and across organizational levels – strategic, operational, tactical, technical. Modelling and simulation is recognized as an important tool for supporting military decision making, e.g. for generating and evaluating potential courses-of-action. For successful application and acceptance of these technologies one needs to take into account the entire decision making 'system', thus including the decision making processes and commanders or operators that make decisions.

AI-technologies can improve this decision making system in various ways. E.g., AI-technologies are used to extract observations from (big) data streams, to automatically build models of the (physical/human/information) terrain, to generate predictions of future events and courses-of-action, to analyse these predictions, to explain results to a human decision maker, and to build a user-model of that human decision maker.

For all these applications AI-technologies can be used and are really starting to be used, under different circumstances and thus subject to different requirements. In this paper we present an overview of the different roles AI-technologies and simulation have in the decision making 'system', with the intent to contribute to an integrated view on AI within our community and to lay a foundation for the various R&D on AI for military decision making.

1.0 INTRODUCTION

Military decision making takes many forms. It takes place in different domains – land, maritime, air, space, cyber – and across organizational levels (see e.g. [7]). For example, on the strategic level decisions are made as to if and when a military mission is started within a specific operational area. On the operational level a Joint Forces Commander decides what military elements are assigned to a certain operation and specifies the desired effects that will be sought in specific operations. On the tactical level, e.g., a maritime task group Anti-Air Warfare Commander determines what frigate should engage an incoming threat. Lastly, on the technical level it is decided what weapon is employed at what range to neutralize an adversary.

Modelling and simulation is recognized as an important tool for supporting these in-the-field decision making processes[1] (see e.g. the inventory made by [3]). It provides a means towards the understanding of complex environments and evaluating effectiveness of potential courses-of-action, without having to use in-field testing. Thus, resorting to modelling and simulation can be safer, cheaper, faster, and different ways of operating can more easily be tested. Furthermore, for in-field military operations it might not even be ethically responsible to try-out extensively how a military operation should take place. For, unintended and unexpected effects would already be done, before commanders could decide not to continue operating according to the same tactics.

Modern modelling and simulation is frequently supported by artificial intelligence (AI) technology. E.g., for simulation of individual, organisational and societal behaviour models (see for some context [13][4]) to gain insight into the plausible and probable behaviour of adversaries. Building on this behavioural insight, smart analysis and decision support for military operations design on many decision-making levels can be provided. Furthermore, AI technologies are used to construct these models, to interact with these models, and to swiftly analyse large amounts of simulation results data. Technological advancements herein are plentiful, e.g. using machine learning to construct more realistic behaviour models [11], improving human-machine collaboration [5], making sense of large amounts of simulation data [10]. Nevertheless, AI technology can and should only be used in military decision-making when it is of use to the decision-maker. This means that integrating AI-technology (in modelling and simulation) should only be done when either the quality of the decisions made increases or the process of decision-making is made easier.

Successful application and acceptance of simulation for decision support – possibly building on AI technology – depends on interaction with and continuous learning from the primary military decision-making processes ([1]). Decision-makers and analysts should know how to ask the right input questions for answering by modelling and simulation. These questions should then be translated into the right output answers by modelling and simulation studies. Therefore a broad, comprehensive view of the interaction between military decision-making processes and military simulation, supported by various complementary AI technologies and subject to different functional requirements, should be available. In this paper we present an overview of the different roles military simulation supported by AI-technologies have in the decision making 'system', with the intent to contribute to an integrated view on AI within our community and to lay a foundation for the various R&D on AI for military decision making.

2.0 MILITARY DECISION-MAKING WITH SIMULATION, A SYSTEM VIEW

As stated in the introduction, decision-making takes place across different domains and different organisational levels. Here we present a schematic view of the decision-making system, to provide a generalised insight into how decision-making can be supported by simulation. This view (Figure 1) is derived from an analysis of multiple decision making processes, such as Joint Targeting [5], operations planning [7], maritime anti-air warfare [1], combined with the well-known OODA-loop [8]. Elements in the view are explained below.

[1] *Next to in-the-field decision making, modelling and simulation can assist decision making for the purpose of concept development and materiel or system acquisition. We consider these applications out-of-scope for our current work.*

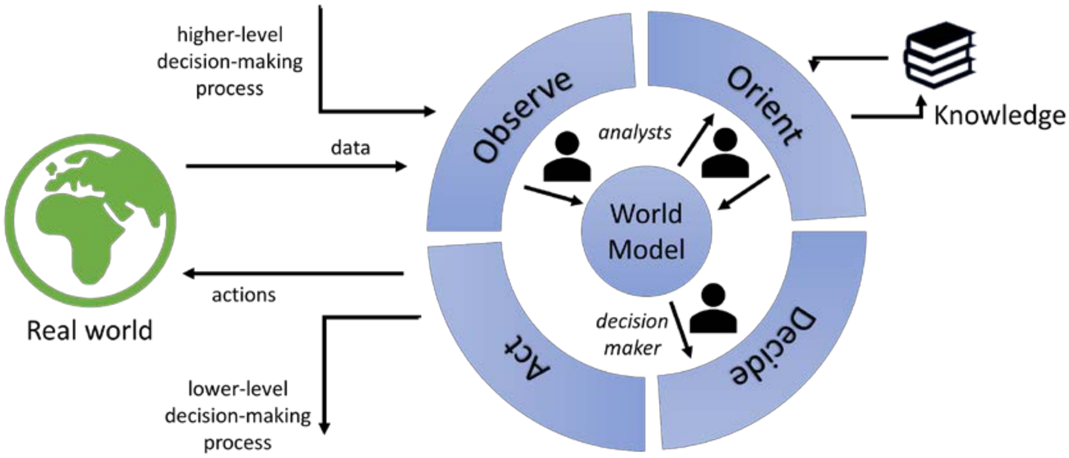

Figure 1: A system view of the military decision-making cycle supported by modelling and simulation.

<u>Observe:</u> The first step in de OODA-loop is observation, in a broad sense, of events and circumstances that are developing and unfolding in the <u>Real World.</u> Observations consist of, e.g., (raw) data from sensors, including our own eyes and ears, and symbolic data from reports, newspapers and social media. Guidance from higher-level command and control entities is also gathered. These data are processed by an <u>Analyst</u>, naming individuals seen on footage, counting occurrences of certain Twitter tags, verifying that a certain event did actually happen, et cetera. According to [9] this can be referred to as Situational Awareness level 1: Perception of elements in their current situation.

<u>World Model:</u> Already during the Observe step in the OODA-loop begins the process of constructing a World Model, either implicit or explicit. Another designation of a World Model that fits the military decision-making point of view is c*ommon operational picture*. All concepts that are relevant are represented in the World Model, including uncertainties and assumptions. Note that the World Model can be simulated, i.e. behaviour of individuals, platforms, groups or societies can be projected over time, even if it is implicitly done in the head of a user.

<u>Orient:</u> During the second step of the OODA-loop the analyst uses his expert knowledge, reasons about observations, forms hypothesis on e.g. the intent of the opponent. By doing so a deeper *understanding* [12] of the Real World is achieved, which is reflected in the World Model (still either explicit or implicit). In terms of situational awareness this is referred to as level 2 (comprehension of the current situation) and the capability of situational awareness level 3 (projection of future status). At any time the result of reasoning can be that the structure of the World Model is insufficient, e.g., an aspect of the Real World that was thought irrelevant turns out relevant after all. As a result the World Model is updated.

<u>Decide:</u> The <u>Decision Maker</u>, that might be the same person as the analyst, will consider options on how to act based on the understanding of the Real World. The *predictive* capability of the World Model is used to play out various scenarios, giving insight into what desirable courses of action are and what are not, or giving insight into what critical points are in space and/or time, such that extra consideration can be given to those. Naturally, if the World Model is implicit this is all a mental effort of the decision maker. Furthermore, the precision and/or certainty with which conclusions can be drawn on projected behaviour of the Real World system of interest differs strongly: from precise routes, to broad indications of likely strategies and doctrine.

<u>Act:</u> During this step of the OODA-loop, actions are executed. These actions take place in the Real World, and then a new OODA-loop begins to observe if the decisions that have been made need to be reconsidered. Another action can be to give an order to a ‘lower level’-decision making process, e.g. for

subordinate units to plan and execute a task that they are given. This is how decision making processes at different organisational levels interact. Also note that, although the World Model at each organisational level is linked to the Real World, the structure of these World Models (i.e., what is considered relevant) might be different.

Conceptually it is straightforward to introduce simulation (and actually first the enormous effort of modelling) in the decision making process as described above. During the first and second step a model of relevant parts of the world is built, which at later times is used to evaluate many different scenario's, analyse the resulting outcomes, and base decisions on the conclusions thereof. As will be shown later on, the roles of AI-technologies relate to the use of modelling and simulation very well.

Although it is conceptually straightforward to incorporate simulation and AI technologies, in order to provide real added value to operations, it needs to be embedded in the specific decision-making process. And each decision-making process is different, with different time constraints, different actors, in different operational environments. This will pose different functional requirements on the solutions, including AI technologies, that are developed to be used. Furthermore, depending on the exact operational decision-making environment the added value (or lack of it) of applying AI-technology will be different. In the next section we present a further exploration, although certainly not an exhaustive effort, on a specific case to allow for a more generic identification of the different roles that such a system could have in the process.

3.0 CASE STUDY: JOINT TARGETING CYCLE

This section provides a first order case study of five ideas on how simulation and AI technology can be employed to support decision-making in (deliberate) joint targeting at the operational level. For each idea the following are described: the actor (decision-maker) and/or product that is strengthened, how AI provides support, and what is the added value of using this form of support. Note that the goal of this case study was to get a better understanding of the breadth in which AI technologies can be applied, thus the goal was not to completely cover all possibilities or to be too detailed. This type of case study has made sure that initial functional requirements can be derived for which AI-technology and smart modelling and simulation should apply.

Figure 2 shows the joint targeting decision-making cycle from the NATO Allied Joint Publication 3.9, wherein the five ideas are highlighted.

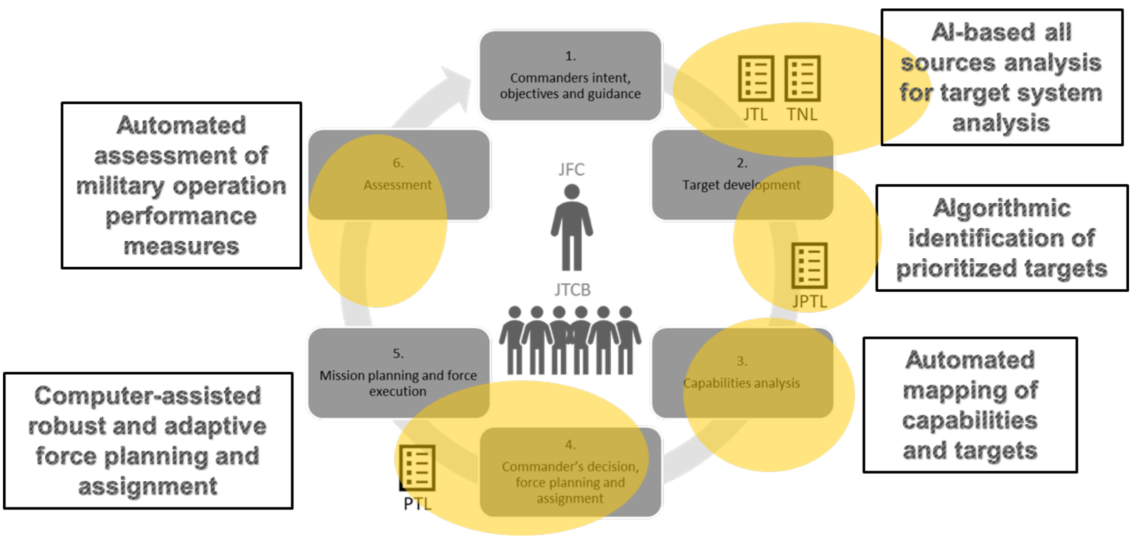

Figure 2 - The Joint Targeting cycle from NATO Allied Joint Publication 3.9, JFC = joint forces commander, JTCB = joint targeting coordination board, JTL = joint targeting list, TNL = target

nomination list, JPTL = joint prioritized target list, PTL = prioritized target list.

Idea 1 – AI-based all sources analysis for target system analysis: The first idea is to support the members of the Target Support Cell that are involved in Target System Analysis within phase 2 of the Joint Targeting Cycle performing target development. Assume, for example, that from phase 1 follows the intent to disrupt the adversaries' funding ability by targeting his oil-production. During phase 2 analysts will study the oil-production target system to identify wells, refineries, pipelines, important roadways, perhaps key people involved, et cetera, based on all sources they have available (imagery, signals intelligence, human intelligence, et cetera).

AI-technologies can assists the human analysts in building the 'target system model', i.e., by employing pattern recognition algorithms to process large amounts of all sources information, by using reasoning algorithms that combine pieces of information in a structured and coherent whole. The algorithm that analyses the incoming information might – after incremental AI-driven innovation – also be able to identify new concepts not reflected yet in the target system model that can then be automatically added to it. Another possibility is to create a 'virtual analyst' (see Figure 3) that assists the human analyst by continuously challenging assumptions, hypothesis, and human biases, which would require additional user-modelling and explainable-AI techniques.

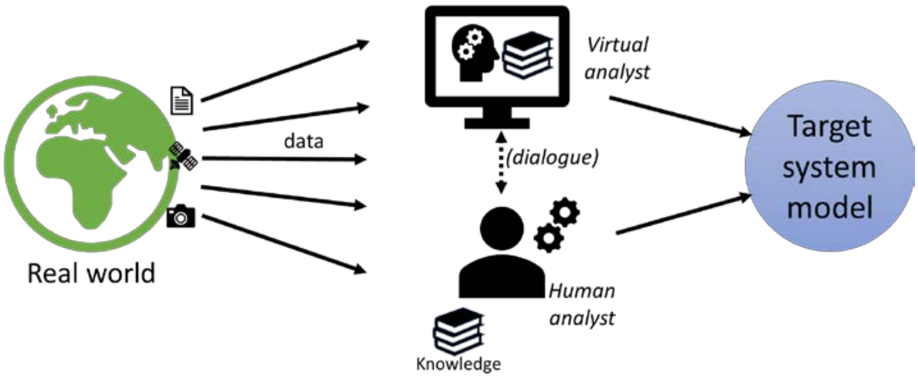

Figure 3: A human and virtual analyst, together interpreting data and reasoning on information and knowledge to build a target system model.

The potential added value of this idea is firstly in completeness, a larger number of targets can be presented to a human analyst – which can still do the last step of target vetting for cross-check purposes. Because all-sources intelligence is integrated into the target identification decision, more specific target information can be derived. After the identification algorithm has been trained, faster and thus more timely identification can be performed than when building on human-eye identification of targets from data. Lastly, the algorithm can explicitly be steered towards the identification of different types of targets that might not all lie within the experience or observation capabilities of human analysts.

Idea 2 – Algorithmic identification of prioritised targets from a target system analysis: The second idea is to support identification of prioritised targets from a given target system analysis. This assists the target support cell members in deriving a joint prioritized target list, which is made in Phase 2, Target Development, of the joint targeting cycle. Support by AI technology starts by translating the target system analysis, if not already, into a computer-understandable form consisting of entities connected by functional relationships, supported by missions goals that are aimed for. Then, the resulting utilities (e.g., effects and duration of effects) from targeting, directly or indirectly, different entities are calculated over the relevant time scale.

The end result can then be checked by a human analyst which possibly redirects parts of the algorithm to make sure that the end-result selection of prioritised targets fulfils and balances the mission goals as good as possible. A separate possibility is that analysis shows that some parts of the target system are not yet understood enough to make a certain decision, and then issues new intelligence requests to reduce this uncertainty.

The added value of using AI technology in this case is firstly in better and faster prioritization through the complete identification of priorities consisting of maximising mission goals fulfilment, while at the same time minimising negative issues. Such comprehensive analysis possibly leads to original target selection, in which counterintuitive yet highly effective targets to be acted upon are found. Traceability of target prioritization increases because the algorithmic specification of the target selection problem and the positive and negative associated utilities forces decision-makers to be completely explicit in eliciting their preferences.

<u>Idea 3 – Automated mapping of capabilities and prioritized targets:</u> Closely related to Target Development (phase 2) is phase 3's Capability Analysis. The third idea is to assist, still supporting members of the Target Support Cell, in finding the best synchronised combination of the most appropriate (lethal and non-lethal) capabilities that can be applied to generate the desired physical and psychological effects. Using simulation and AI-technologies to automatically generate and play through both high-level and low-level courses of actions a profound understanding of the strengths, opportunities, weaknesses and threats of plans is gained. Of course, building such an understanding is only useful if done in close collaboration with human analysts and decision makers, requiring technologies for human-aware 'virtual analysts'.

<u>Idea 4 – Computer-Assisted Robust and Adaptive Force Planning and Assignment:</u> In phase 4 of Joint Targeting the results of capability analysis are integrated in further operational considerations, leading to a final approval of targets by the Joint Forces Commander. Simulation and AI optimization technologies can be used to find the best assignment of scarce resources to targets or other tasks. What is considered 'best' can vary, e.g., striving for maximum effect, safety, robustness, flexibility, or any combination of these and more factors. This might provide original planning and assignment solutions, that would partially be counterintuitive from the viewpoint of the human analyst, yet productive. Intelligent optimization algorithms can help identify key points in time and/or space that are worth monitoring. And if real-time tracking of progress is possible, immediate re-assignment options can be generated before events or opportunities actually occur, reducing decision making time in time-critical situations.

<u>Idea 5 – Automated assessment of military operation performance measures:</u> During the final phase of Joint Targeting, data and information is gathered and analysed to determine to what extent planned actions are executed (measure of performance) and the intended effects are being reached (measure of effect). Because this type of analyses is largely similar to the ones performed during other phases (i.e., they require observations and understanding), simulation and AI technologies employed there can be reused. For example, a 'target system model' can be used to determine, beforehand, what measures or combination of measures are most indicative of performance and/or success, perhaps taking into account other factors such as measurability and delays of effects. These insights can be used to steer e.g. battle damage assessment efforts. Algorithms can generate multiple hypothesis automatically and when data/information is available 'virtual analysts' can assist in reasoning on these hypothesis and information, helping human analysts interpret complex situations better and in a structured manner.

4.0 DISCUSSION: ROLES OF AI IN MILITARY DECISION-MAKING

In this section we will discuss the roles that AI technologies can play in military decision making and relate these roles to the military decision making system presented earlier. These roles have been synthesized from the case study above. The different roles are structured along two levels, from top to bottom: at the 'process' level where different but coherent steps/phases are executed, and at the 'individual' level where a human (or a team) is responsible for execution of a specific step of the decision making process.

At the level of the entire decision-making process multiple steps are distinguished. In the system view on decision-making presented earlier these are Observe, Orient, Decide and Act. In the Joint Targeting case study these correspond to six phases, performed by different people at different times. At this level we define four *functional* roles for AI technologies to support the decision-making process:

- <u>Sensing:</u> AI technologies in this role, mainly in the form of pattern recognition, aid in processing large amounts of data, such as finding people in imagery, detecting anomalies in data streams, et cetera.
- <u>Situation understanding:</u> The function of this role is to achieve understanding [12] of the current or a hypothetical operational environment, thus describing all relevant entities, the relationships between them, and unobservable attributes such as their ambitions and goals. For example, reasoning on available pieces of information on recent hostile activities combined with general knowledge on their doctrine, can be used to generate hypothesis about their most likely intent.
- <u>Plan generation:</u> In this role AI techniques, e.g., search and optimization, are used to generate plans, policies, and courses of action that aim to reach (or avoid) a certain goal situation. Handling meta-criteria, such as plan robustness or situation utility are also part of this role. And evidently, in many cases uncertainty will be inherent to the operational environment and can therefore not be ignored. Nevertheless, the better the understanding of the current situation, the better the predictive capabilities.
- <u>Learning:</u> AI technologies in this role are used to update *knowledge* about the operational environment. For example, at a certain point in time one might find that an assumption on enemy doctrine that was considered correct, is no longer valid. In order to be able to maintain proper understanding, this new knowledge should be reflected in all other decision-making steps.

At the individual level a single step of the decision making process is executed, typically under the responsibility of one or a team of human analysts and/or decision makers. Regardless of what that step entails, AI technologies can be employed in different *collaborative* roles to support the human(s):

- <u>Expert system support:</u> In this role support is shaped like a classical expert system, providing the human decision maker or analyst with advice in the form of knowledge and optimisation results. Important considerations are, for example, how this advice is presented to the human in such a way that he can accept it. Research in Explainable AI might be a direction to pursue.
- <u>Virtual team member:</u> In this role AI technologies are used to create an interaction between the human and a support system in a more equal relationship, actively working on a common goal. For example, the virtual team member can aid the (cognitive) process of coming to a decision by asking questions to make assumptions explicit or to challenge biases. Research in Human Aware AI might be a direction to pursue.
- <u>Autonomous decision making:</u> Another possible role for AI is to replace a human decision maker or analyst in a step of the decision making process. Depending on the interaction with other steps in the greater decision making process, the same considerations of expert system and virtual team member support are valid. E.g., humans in other decision-making need to be able to thrust an autonomous system.

Figure 4 shows the seven roles of AI plotted in the military decision-making system view. When using simulation and AI to support the decision making process one should always consider how these different roles interact, both at the process level and at the individual level. At the process level of for example Joint Targeting, Phase 2 includes both Orient (target system analysis) and Decide (what to target for desired effect). Phase 3 also includes both Orient (own capabilities) and Decide (how to bring the desired effect). Theses phases share the same world model, and it is not unthinkable that the introduction of AI support to this process will lead to a merger of these steps. At the individual level, e.g. considering Phase 2 again, analysts can be supported by integrated situation understanding, plan generation, and learning technologies, and any combination of virtual team member and expert system support technologies.

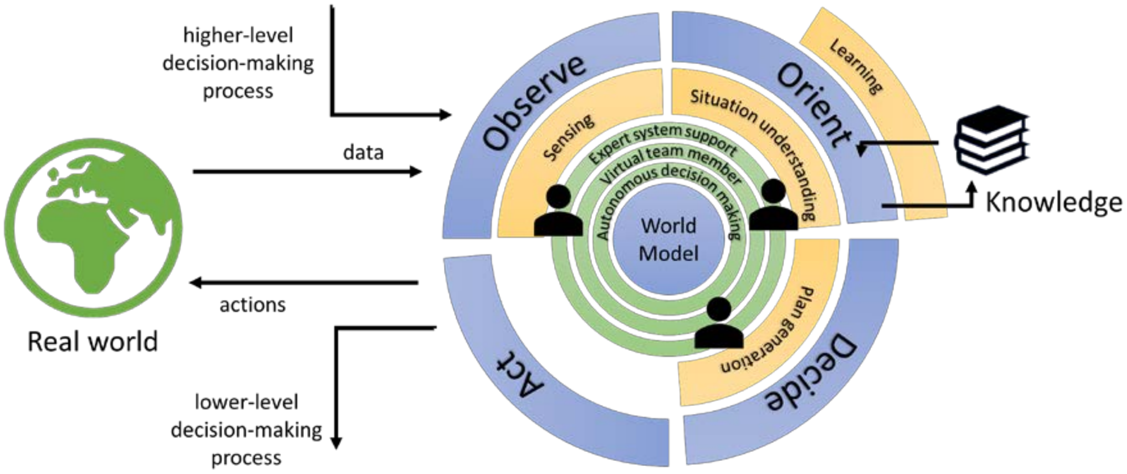

Figure 4: A system view of the military decision-making cycle supported by modelling and simulation, wherein functional (yellow) and collaborative (green) roles of AI-technology are depicted.

5.0 CONCLUSION AND FURTHER RESEARCH

In the first section of this paper we introduced a system view on military decision making, largely based on the OODA loop, wherein we introduced the World Model as a central means for providing modelling & simulation support to the complete decision-making cycle. Next, from our Joint Targeting case study we deduced seven functional and collaborative roles whereby AI can contribute to military decision making. These roles correspond to either decision making steps or to how support is provided to a human responsible for the process step. Finally, we integrated these AI roles in the decision making system view.

The goal of this paper is to contribute to an integrated view on AI within our community and to lay a foundation for the various R&D on AI for military decision making. When developing simulations and AI in support of military decision making, we recommend to consider both the process level and the individual level. At the process level benefits are gained from using modelling & simulation. At the individual level practical support is provided to human analysts and decision makers, and AI technologies can contribute to this in a combination of different roles. Given that individual steps of decision making processes are all different and pose different requirements, the AI-technologies to fulfil these different roles need to be developed as an integrated whole.

We believe that, with more research committed to this subject, both the speed and quality of military decision making can be improved. It is however very important to keep a constant eye on the added value of specific prospective AI applications, as well as looking into the implications these applications can have on, e.g., the required skills of the people responsible for the process, or even the process itself. The last needed is a system that is there because it *can* be build, rather than that someone is helped. For this, the question of how to qualify and then quantify the added value of applying AI for a specific military decision-making application should be answered more generally. Such insights would, in turn, be valuable input for a collective technology roadmap on AI for military decision making.

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