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Sociotechnical System Perspective on Artificial Intelligence Implementation for a Modern Intelligence System

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A Sociotechnical System Perspective on Artificial Intelligence Implementation for Modern Intelligence Systems

Abstract

Implementing new technology into a sociotechnical system, such as a military intelligence system, is a challenging enterprise. The needs and expectations of the “social” users are critical in designing and implementing the technical system to support the intelligence process. New technology often affords new ways of accomplishing the objectives of the intelligence process. However, possible process and operation improvements may be constrained due to the tendency of users to stick to the entrenched doctrine of strict hierarchical operation, typical of military organisations. This paper presents a sociotechnical system’s perspective to guide implementation of new technology, such as Artificial Intelligence (AI), in an existing Military Intelligence System. This framework is based on contemporary sociotechnical system development and Cognitive Work Analysis (CWA) literature, which is adapted to the field of intelligence systems.

1 Introduction

Due to the complexities of modern conflicts, traditional military intelligence approaches and tools are becoming increasingly inadequate at satisfying the decision support requirements of commanders and other decision makers. These complex conflicts tend to be in the “grey zone” of irregular, unconventional, hybrid, and political warfare. In these scenarios, adversaries seek asymmetric advantages over traditional military power to achieve political objectives. Global interconnectedness of the twenty-first century, combined with political, economic, and social changes, increase the scale of complexity (Smith 2016).

In parallel to the complex modern battlefields, the ever-growing Internet of Things (IoT) and social media platforms dramatically increase the available information to be processed and analysed as intelligence. The abundance of information is impossible for humans to effectively analyse unassisted. Intelligence analysis systems require Artificial Intelligence (AI) tools to dredge through the information for finding the patterns and making predictions. AI is the intelligence exhibited by machines that perceives its environment and takes actions that maximize its ability to achieve a goal (Suri et al. 2016).

The field of AI is a wide area of study that includes the development of big data, predictive analytics, cognitive computing, and deep learning. AI can support the development and testing of hypotheses during intelligence analysis. This implies that a machine mimics the human “cognitive” functions, such as learning and problem solving. Globally, AI is increasingly exploited for military applications, including surveillance, reconnaissance, intelligence analysis, command and control, threat evaluation, cyber security, and training (Svenmarck et al. 2018).

Decisions should be supported by accurate intelligence based upon analysis of gathered information. However, decision-making within combat operations can be characterised as having a “high regret” if the “wrong” decision is made. Implementing AI tools in intelligence systems require a careful consideration of these difficulties to improve the trust of commanders (Pearson et al. 2018). Many AI systems operate as a black box with insufficient transparency into the inner workings. Decision makers also require expert knowledge in data science to interpret the AI algorithms (Svenmarck et al. 2018). Unfortunately, the intelligence community tend to resist new technologies (Byman 2016).

Intelligence systems can be viewed as a complex sociotechnical system as it consists of people working in a social structure to perform tasks using technology (Baxter & Sommerville 2012). Implementing a new technology in a sociotechnical system has its own set of challenges. The emerging enabling, sensing, computation and communication technologies create a larger design space with greater complexity. Therefore, changes in technology also require changes to traditional intelligence processing practices (Valle-Klann 2013). The sociotechnical system’s theory considers humans as assets that enhance a technical system through learning and adapting. Technology should not aim to replace humans, but rather to assist them to achieve their goals (Read et al. 2018).

This paper reviews the literature on the intelligence process, AI and sociotechnical systems to provide a framework for the implementation of modern technology into an intelligence system. This framework will be used to help defining requirements for future intelligence analysis systems. The paper concludes with a high-level proposal of the framework, using Cognitive Work Analysis. This framework also incorporates lessons learnt from a recent field experiment with a web-based collaboration concept demonstrator as part of a future

Intelligence System. Experience with the concept demonstrator highlighted the need to expose military intelligence system operators to a new way of working.

2 Sociotechnical Systems

Fred Emery and Eric Trist developed the concept of sociotechnical systems in the 1950s. That period saw a dramatic increase in technology commercialisation due to developments from World War 2 (Miller 1998). However, the introduction of new technology in existing organisations to improve efficiency and productivity, did not meet expectations. Since this period the sociotechnical systems theory became prominent along with the evolution of information technology.

As seen in Figure 1, the sociotechnical theory acknowledges the interrelatedness of social and technical aspects for technology application in an organization. Interaction between the social and technical systems have linear, as well as non-linear, “cause and effect" relationships. These interactions may create the conditions for either successful or unsuccessful system behaviour. Therefore, the sociotechnical approach focusses on the joint optimisation of the social and technical subsystems (Baxter & Sommerville 2012, Bostrom & Heinen 1977, Trist 1981, et al. 2015). The sociotechnical system is also an open system that exists within a complex environment, which it interacts with and is affected by (Walker et al. 2008). This causes the sociotechnical system to be a complex system as these interactions cause nonlinearity, emergence, feedback, and self-organization (Bowman 2015).

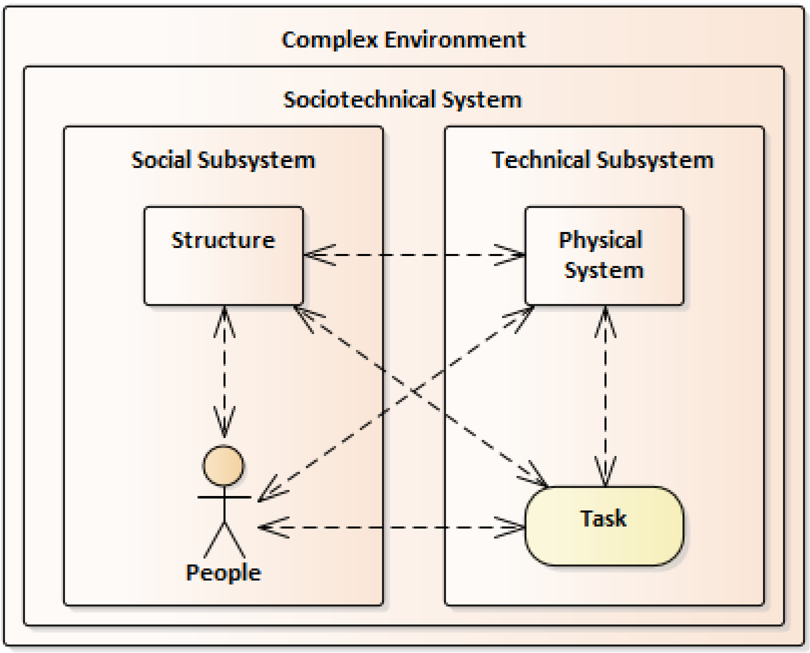

Figure 1: Sociotechnical System (Bostrom & Heinen 1977)

The social subsystem addresses the structure of the organization, encompassing the authority structures and reward system, as well as the people in the organisation with their knowledge, skills, attitudes, values and needs (Bostrom & Heinen 1977). People perform work using the available technological artefacts, to achieve economic performance and job satisfaction. The technological artefacts consist of the tools, devices and techniques that transform inputs into outputs. Trist and Bamforth (1951) highlighted the principles of sociotechnical systems as responsible autonomy, adaptability and meaningfulness of tasks (Baxter & Sommerville 2012, Maguire 2014).

The sociotechnical theory aims to promote knowledge sharing, learning and innovation within the organizational context, to enable collaboration and flexibility for a competitive advantage (Walker et al. 2008). New communication and knowledge management technology afford new opportunities for information flow within organisations to achieve its goals. Therefore, changes in technology may affect how the people interact and it may cause changes in their values, cognitive structures, lifestyles and habitats. It is therefore important to be formative in the system analysis and development approach (Carroll & Rosson 1992). The sociotechnical system must be designed to evolve in changing environments through interactions among social and technical elements (Drăgoicea 2015). The way that humans think, operate and interact must be captured in the physical system design. The design of a sociotechnical system can be approached from the following perspectives:

1. Human-centred perspective. Technology should alleviate the workloads of humans to achieve situational awareness in support of decision-making. Automation may be useful during normal situations, but may be cumbersome during complex and unforeseen circumstances (Waterson 2002).
2. Team-oriented perspective. A team is defined as two or more parties that interdependently work together towards a common goal. Technology is also a team member. Trust between team members is a major factor for success (Salas et al. 2008).
3. Work-oriented perspective. The focus on the work in the sociotechnical system helps to delineate the work and tasks across the team, which consists of machines and humans. Work is seen as purposeful activity acting upon and in response to a dynamic environment (Rasmussen et al. 1994, Vicente 1999).

A modelling approach for assessing the impact of a new technology on a complex sociotechnical system has been developed and demonstrated by the authors through previous publications (Oosthuizen & Pretorius 2013, Oosthuizen & Pretorius 2014, Oosthuizen & Pretorius 2016). The remainder of the paper will focus on how to apply sociotechnical principles to develop intelligence analysis systems capable of solving the contemporary complex problems.

3 Modern Military Intelligence System

A Military intelligence system aims to improve decision-making by reducing ambiguity and uncertainty about deploying resources to achieve objectives. The intelligence system provides tools (technologies) that enable analysts to process data from one form to another for making sense of noisy or obscure concepts. Traditionally, the intelligence process mainly focussed on filtering, storing and enabling retrieval of information. This placed the analyst at the centre of the information flow to receive information, hunt for the missing bits, filter and prioritise the information to collate and manage the knowledge base (Hare & Coghill 2016, Byman 2016).

A customer or decision maker poses a question (problem statement), for supporting a decision, to initiate the intelligence process. From this, the analyst identifies and constructs hypotheses to identify possible truths. The analyst tests the hypotheses by subjecting it to the data. Typical intelligence processing tasks include requesting, analysing, drafting, editing, and finally publishing information as intelligence. Analysts need to apply a range of information processing tools to add value to data while applying reasoning and creativity skills. The success probabilities of different hypotheses are compared to each other using the processed data. The analyst shares the information and intelligence product with the decision makers. This should be an iterative and interactive exchange of information. The information is visualised for the decision maker for interpretation and understanding (Hare & Coghill 2016, Byman 2016).

Intelligence analysts should approach problems like social scientists instead of examining only one possibility. They have to search for information to support answering the hypothesised question. However, finding the required information may be a complex problem (Hare & Coghill 2016, Byman 2016). The intelligence process requires a networked, collaborative and flat structured organization for various analysts to collaborate. A strict vertical intelligence hierarchy is still useful in a scenario with constricted information flows and a single (simple) purpose. With the IoT, more information is accessible for all. In a hierarchical structure, this creates organizational friction (Hare & Coghill 2016).

From a sociotechnical perspective, the implementation of new information technology in a military intelligence system should affect the analysis workflow, required skills, and organizational structure. The analyst must be able to tailor and evolve the intelligence workflow and processes to adapt to environmental constraints such as problem complexity, time available as well as type and quantity of information (Hare & Coghill 2016).

The authors have practical first-hand experience about the sociotechnical impact of implementing of a new technology in an intelligence system. The current system as developed 20 years ago, implemented cold war age intelligence processes. The technology only automated the distribution of information. Analysis tools in the system are lacking. The new web-based collaboration technology aims at improving the visualisation and distribution of information in the form of geo-located events. The new technology also includes a basic data analytic capability.

Often, with the implementation of a new technology, the complexities only become clear once problems occur in real life. Deploying the technology in a military intelligence system necessitated the constriction of information flows to fit the entrenched doctrine and processes. This limits the possibilities and advantages of the new technology. It also took time for operators to accept the new technology into the social structure of the intelligence system.

4 Artificial Intelligence in Military Intelligence Systems

The intelligence community is experiencing a period of dramatic change due to the 4th Industrial Revolution. Improvement of information technology capabilities provide access to more information, up to the stage where Big Data has become a common theme. The IoT, with an increasingly sensor-rich and connected environment, provides an endless source of data that outstrips the assimilation capacity of humans. Instead of triaging information, the analysts need to use new automated searching, indexing, categorizing and structuring technologies. Fortunately, the information processing technology, with the resurgence of AI, has also advanced to stay abreast of the new abundance of data.

AI performs activities associated with human thinking such as decision-making, problem solving, and learning. It also includes intelligence facets, such as perceiving objects, natural language processing, and storing of knowledge. Machine learning is a subset of techniques required to achieve AI. Deep learning is a current machine learning approach that constitutes a representation-learning method with multiple levels of representation by combining simpler but non-linear models (Dellermann et al. 2019).

The performance of AI is continuously improving to achieving super-human abilities in various tasks such as playing complex games, cancer detection, or autonomous driving. However, machines cannot yet solve problems that require creativity and expertise for decision making and planning independently. Machine learning systems still require human common sense and insight to train models in supervised machine learning approaches. Even unsupervised machine learning requires a human to make sense of clusters and patterns identified the in data, to create knowledge (Dellermann et al. 2019).

The complementary and divergent capabilities of humans and computers can be integrated to augment each other. Computers are good at performing mundane and repetitive tasks that require fast processing of huge amounts of data. They also excel at recognizing complex patterns and weighing multiple factors using consistent rules. AI may improve human decisions by providing predictions from automated tasks, which are difficult for humans. Humans employ common sense and intuition while being adaptive, creative and flexible.

Human intelligence and domain knowledge are key elements in the AI loop. Humans have to generate, train and debug machine-learning models and algorithms. They also need to make sense of unsupervised approaches such as data clustering. Machine learning requires massive amounts of structured training data as opposed to humans, who can learn from only few “soft data” examples. Inadequate control of the AI learning process may cause unintended consequences and limit interpretability. Trust in the output of AI is one of the most challenging barriers to the new technology adoption. A balance between trust and distrust is required to leverage the potentials of AI while ensuring that possible negative effects due to overreliance is avoided. This reiterates the requirement for humans to remain in the loop of the machine learning process (Dellermann et al. 2019).

Solving real-world problems through intelligence analysis by AI systems require a continuous and collaborating sociotechnical integration of humans and machines. Therefore, humans and machines have to perform as “team mates”. This requires a deliberate allocation of tasks among AI and human agents of the intelligence system. Both can co-evolve through learning to achieve improved outcomes at a sociotechnical system level. Human involvement helps to control the AI learning process to ensure it makes inferences based on human interpretable criteria. The effective integration of complementary heterogeneous intelligence agents (humans and machines) as a “whole” sociotechnical system may overcome current limitations (Agrawal et al. 2018, Dellermann et al. 2019).

5 Sociotechnical Framework for a Modern Intelligence System

This section presents a framework to support developing a modern intelligence system using sociotechnical principles. Any sociotechnical system framework has to emphasise the interrelatedness of the system components; people, tasks, structures and technologies for joint consideration (Davis et al. 2013). A typical intelligence work system usually comprises an interdependent social system (e.g. the people, roles, working practices, culture and goals) and technical system (e.g. physical infrastructure, tools, technologies and process tasks). Changes to one part of the system may necessitate changes to another. The military intelligence system also has to consider the wider context of doctrine, regulatory framework, stakeholders and the opposing force (Davis et al. 2013, Hughes et al. 2017).

5.1 Sociotechnical System Parameters

This section presents the sociotechnical system parameters to be included in the framework. The parameters have been derived from the discussions above on Sociotechnical Systems, Intelligence Systems and Artificial Intelligence.

5.1.1 People

Users and other stakeholders have experience in military intelligence practicalities to inform system design. In addition, the expectations of different age-groupings affect implementation of new information technology. The younger generation tends to be more comfortable with new technology and its interaction as they grow up with it (Maguire 2014, Hare & Coghill 2016). An intelligence system is cognitive-heavy and should consider the social contribution of individuals and groups. The design of the system has to cater for the different skills levels and specialisations required for the roles and functions in the system.

The interaction between human analysts and AI machines can also be viewed “social” in the extreme sense. Humans provide input by annotating data for training a model and verification of the machine output. This teaching input can be both explicit and implicit. Explicit teaching leverages active input of the user through labelling of data while the adaption of user demands presents implicit teaching (Dellermann et al. 2019).

Intelligence analysts require different skills than before to cope with the increasing complexity and uncertainty of current and future problems. Historically, deductive reasoning, which works from a known to an unknown, was adequate. However, deductive reasoning does not apply when facts are lacking. The analyst also requires inductive and abductive reasoning skills and methodologies.

Inductive reasoning explains what might be true, given an incomplete and unstructured set of facts. It interprets collected information to proposing a theory, similar to solving a puzzle. Intelligence analysts must be able to see the interactions between components as well as between components and their environment. Relationships are important as they provide positive or negative feedback between entities. As the feedback changes, the nature of the relationship can change with it (Bowman 2015).

Abductive reasoning is more of a creative, intuitive process. It takes an incomplete set of observations and tries to provide the likeliest explanation, similar to a medical diagnosis. Abductive reasoning is compared to resolving mysteries (Smith 2016). Analysts should identify the “signals” in the environment in order to anticipate emergent behaviour. The new skills set is similar to operational researchers, engineers, scientists and economists. The traditional skill of formal briefing has become less important (Hare & Coghill 2016).

5.1.2 Task

A workflow coordinates the work of the people. Implementing a new technology can disrupt the established overall work processes, causing users to struggle. Optimal system behaviour requires adjustment of task distribution between humans and machines (Baxter & Sommerville 2012). In a modern intelligence process, analyst need to apply their creative skills for hypothesizing about a problem, analysing the available information, and communicating the results at a greater pace than before.

The new tasks allocated to humans require different skills than before. The typical new intelligence analysis tasks include recognition, prediction, reasoning and action. All tasks require some form of shared data representation, which can be different for the human and the machine. System design must explicitly match human skills and roles with the process and tasks. Intelligence analysts require a new set of skills and qualifications to fit the allocation of tasks between humans and AI (Dellermann et al. 2019).

5.1.3 Structure

The structure of a sociotechnical system is the work setting, which describes the environment where the work and interactions take place. This physically organises the flow of the intelligence process and communication between the operators (Baxter & Sommerville 2012). The system structure affects competition and cooperation between system users. A strict hierarchical structure may result in information silos and limit the horizontal flow of information. Sociotechnical systems tend to be open systems, as they have to deal with diverse sources of information embedded in their environment (Drăgoicea 2015).

5.1.4 Technology

Even though all the aspects discussed above need to be considered while implementing a sociotechnical system, the technology driving the change remains one of the key focus areas. The limitations of the human brain is often the bottleneck in intelligence systems. AI tools can perform complex and repetitive cognitive tasks to increase the effectiveness of intelligence analysts in an information-abundant environment. These tools need to shrink and structure the information pool to a size that can be ingested by analysts. AI tools can interpret an analyst's intent to filter information for the most appropriate items (Hare & Coghill 2016).

Information displays have to reduce analyst's cognitive load through mapping, timelining, charting and other methods. Inference tools to construct and test hypotheses are also required (Hare & Coghill 2016). Employing a prototype of the concept solution for the operators to experiment with can capture sociotechnical requirements for improvement before final implementation (Baxter & Sommerville 2012).

An AI machine makes explicit recommendations to the human analysts. This "machine feedback" supports algorithm optimization and enables humans to predict behaviours with a probability attached. Interpretability of machine output is crucial to prevent biases, and achieve reliability and robustness in the context of AI safety. Algorithm transparency and interpretability of the global model and local prediction help creating trust (Dellermann et al. 2019).

5.2 Cognitive Work Analysis

Multiple perspectives and viewpoints on the system are required to detect emergent properties of system changes for improving system flexibility (Stanton & Bessell 2014, Kant 2018). Sociotechnical systems analysis utilises a variety of tools, however some existing tools have been criticised for being too academic, and impractical to implement in practice (Hughes et al. 2017). Cognitive Work Analysis (CWA) is an approach to analyse and design sociotechnical systems (Baxter & Sommerville 2012).

CWA acknowledges that systems are inherently complex, requiring multiple perspectives on the problem to fully appreciate the relationships between the social and technical aspects. Work is defined as an activity aimed at accomplishing something useful with a purpose, values and success criteria. Flexible design is required to support people executing the work, while adapting to unforeseen and changing environmental conditions. This highlights the need for cognitive analysis and modelling of the work environment. CWA provides a comprehensive modelling framework of analysis to uncover requirements, constraints, and implied (hidden) affordances in the work environment. The theoretical roots of CWA are in systems thinking, adaptive control systems and ecological psychology (Lintern 2009, Naikar et al. 2006, Vicente 1999).

CWA provides multiple perspectives on the activities in the system at a number of levels of abstraction. The CWA framework is a formative and constraint-based approach that models possible system behaviour, rather than only describing actual behaviour, or prescribing normative behaviour (Jenkins et al. 2009, Stanton & Bessell 2014, Kant 2018). The CWA process starts with a focus on understanding the ecological elements, before relating it to the cognitive capabilities of the humans to enable flexibility, which helps to reduce the cost of development (Vicente 1999). The ecological constraints still allow for a variety of work patterns to solve unexpected problems and situations resulting in a flexible decision support.

Products of CWA define the required information content as well as the applicable context where it is used within a cognitive system (Naikar et al. 2006, Vicente 1999, Jenkins et al. 2009). CWA has been applied to analyse complex systems including military command and control, nuclear power generation, health care, disaster management, and road and rail transport. The insights gained from the analysis can be translated into design specifications. The design concepts also need to be evaluated using concept demonstrators to guide selection of the most suited solution (Read et al. 2018). The five phases of CWA are described below.

5.2.1 Work Domain Analysis

The Work Domain Analysis (WDA) defines the problem and solution space of the sociotechnical system, independent of specific instantiations. WDA provides the foundation for understanding its functional structure and the environmental effects on work. The process elicit and present information on the system from existing documentation and expert users. This analysis uses an abstraction decomposition space to model the work domain, not the system implementation, by identifying the goals and purposes of the cognitive system in providing a reasoning space about the environment (Jenkins et al. 2011).

The abstraction dimension is a top-down (global) view of human operators trying to achieve the goals and fulfil the overall purpose of the system. This is integrated with a bottom-up view of available physical resources. The means-ends relationship between the physical resources and functionality highlights possible problem-solving strategies as well as how individual components affect the overall system purpose. This is useful where technical systems, the environment and people interact dynamically to result in many possible instantiations with multiple options for action to fulfil the purpose of a system (Naikar et al. 2006, Vicente 1999, Jenkins et al. 2011).

The top three levels of the hierarchy address the domain independently of the technology used in the system. The bottom two levels consist of the physical objects and the functions they perform in the system (Jenkins et al. 2011). The levels of the abstraction decomposition space are the following:

1. System Purpose. This provides the reason for developing this specific cognitive system.
2. Values and Priorities. The reasoning process requires performance measures, principles, standards, or qualities, to be maintained while executing the process.
3. General Functions. This level provides the domain functions, also referred to as "general functions", required to execute the work in satisfaction of the system purpose. These functions must be performed independently of the physical elements utilised, and can be used to generate scenarios for using the system.
4. Physical Functions. The physical objects implement physical functions through activation or usage. The SE process will relate the functional requirements to the physical functions.
5. Source Objects. These are the physical elements present in the work domain available to perform the work.

The WDA in Figure 2 maps the function allocation of automation on domain structure of a generic military intelligence system with AI technologies. The other phases of CWA will illustrate the behaviour of the sociotechnical system (Li & Burns 2017).

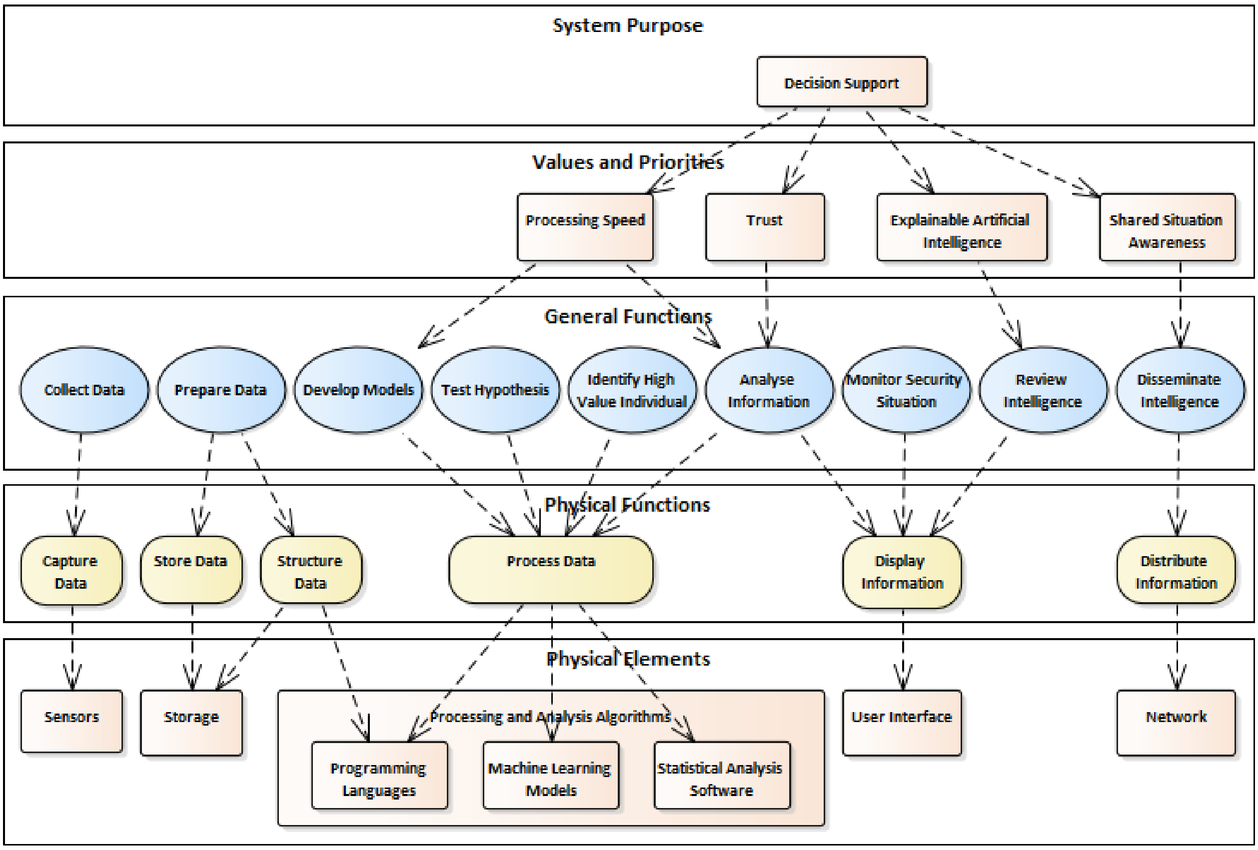

Figure 2: Abstraction Decomposition Hierarchy for AI in an Intelligence System

5.2.2 Control Tasks Analysis

In a complex sociotechnical system, sets of activities may accomplish a goal in different ways. The Control Tasks Analysis is useful in identifying the different combinations of work tasks performed under specific conditions. These activities consist of a set of work situations and work functions that depend on different decisions or control tasks. The control task analysis focuses on the work requirements and constraints limiting achievement of the purpose identified in the WDA. It identifies the information and relationships required for solving specific situations. The decision ladder from Rasmussen (1986), as seen in Figure 3, represents the work situations, problems, states of knowledge, information processing, and their interconnections.

The Control Tasks Analysis models information processing by mapping the task stages onto a decision ladder and exploring various possible shortcuts. The Decision Ladder is a template to identify activities and state transitions. It is not a decision-making process or model (Lintern 2009, Li & Burns 2017). The decision ladder will be useful to identify the possible contribution and roles of AI in the intelligence process. As AI is applied to assist the intelligence analyst, specific transitions and shortcuts can be discovered. These will guide the implementation of AI in the intelligence sociotechnical system.

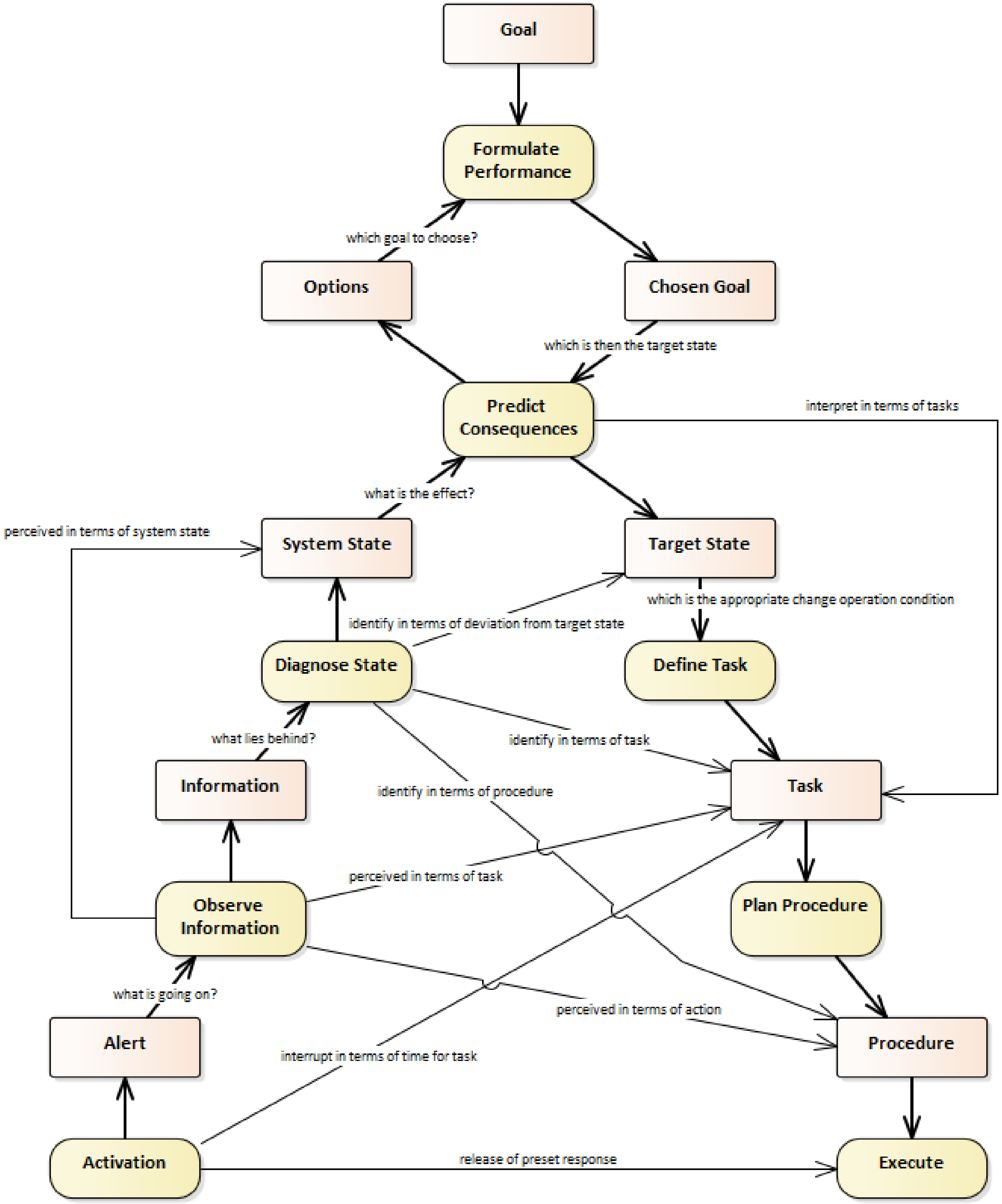

Figure 3: Decision Ladder

5.2.3 Strategies

The cognitive processes identified in the decision ladder are further analysed to determine the strategies for executing the tasks by experts and novices. Contextual factors often affects the patterns of activities that are available to complete a task. System resilience depends on the human employing different cognitive control modes to adapt to changing situational contexts. The typical strategies include a snap decision, searching for recommendations or inferring the most suitable solution from structural principles. The knowledge of how and why workers may choose between different strategies is useful in designing a cognitive system. The output of the cognitive strategies analysis is a detailed description of potential strategies and their application to execute the cognitive processes in an information flow map (Vicente 1999, Lintern 2009).

5.2.4 Worker Competency

Worker competency analysis links the cognitive constraints and preferences of humans and provides a method to design the system. This analysis enables allocation of functions, based on the current human capabilities to achieve the work. To assist in problem solving, humans form a mental model of their environment as part of understanding the situation. This is achieved through a mix of sensory-motor responses, actions based on experience and basic rules, as well as an internal representation of underlying characteristics (Elm et al. 2003). Rasmussen, Pejtersen, and Goodstein's Skill-based, Rule-based and Knowledge-based (SRK) framework maps the decision-making strategies used in controlling a system (Rasmussen et al. 1994). The SRK is another useful framework to identify the contributions of AI in the intelligence process. AI tools can support and enhance the activities in the framework. The SRK framework helps focussing on user interfaces and representations for human and automated system integration (Behymer & Flach 2016).

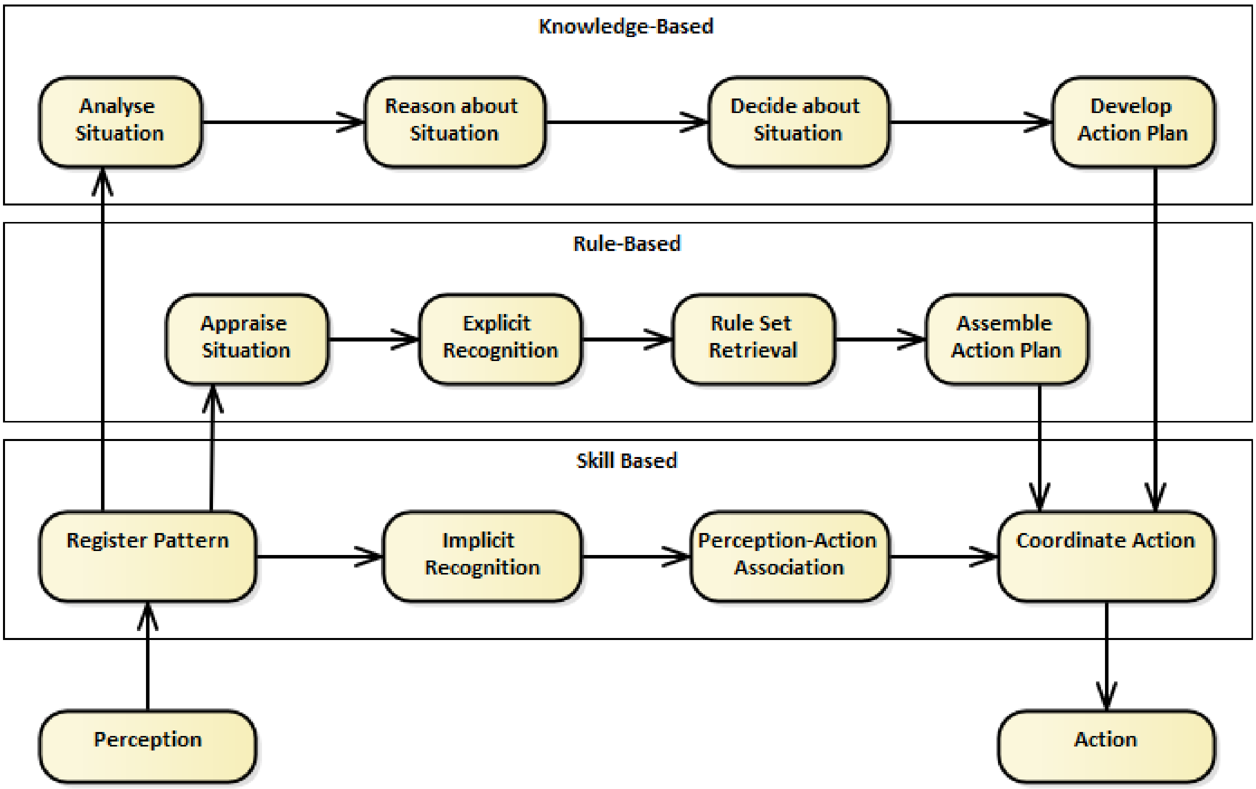

Figure 4: Skill-, Rule-, and Knowledge-based Cognitive Processing

5.2.5 Social Organisation and Cooperation

The aim is to design effective organisations or structures with the required technologies that support communication demands. The interaction and roles of diverse distributed human and technical functions in the complex sociotechnical system must also be analysed. A social transaction transfers some element, such as information, between agents. The social organisation and cooperation analysis focus on the content and form of these interactions. This includes considering the ability and requirement for formal structures and self-organisation of the sociotechnical system.

Social Organisation and Cooperation lists the coordination, responsibilities and roles of the different entities, as well as the information exchange needs. Within the cognitive domain, interaction exists between peers, as well as between management and workers. Processes and technologies are required to support these informational interactions. This collaboration (lateral) and coordination (vertical) can be characterised in terms of the transactions performed (Vicente 1999, Lintern 2008).

6 Conclusion

The purpose of this paper is to develop a framework for implementing AI into an intelligence system. The intelligence system must be able to cope with the complexity of the operational environment that it aims to make sense of, with the abundance of data that is available.

The CWA provides the methodology to analyse the system and the roles AI can fulfil. This enables system designers to ask the right questions to the stakeholders about their requirements for an improved intelligence system. Implementing the CWA with a Model Based Systems Engineering methodology and supporting tools (with a modelling language like SysML) for traceability and requirement management, will also improve the process.

Following this framework will help system users and designers to manage the risks and concerns about the possible flaws of AI. Considering AI as another “social” and flexible system element with skills and shortcomings, which interact with the humans in the system, will go a long way towards gaining the trust of analysts and decision makers.

The intelligence system users should be flexible with their processes and structures to ensure the maximum AI contribution. This framework should also be applicable to other command and control systems as they are also considered to be complex sociotechnical systems.

Future research will focus on applying the framework on actual intelligence systems that start implementing AI in their processes.

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