Modelling Cognitive and Affective Load for the Design of Human-Machine Collaboration

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Abstract. We are developing models for hybrid human-machine systems that can cope autonomously with unexpected, complex and potentially hazardous situations. The synthetic or electronic partner (*e*Partner) has to acquire and maintain knowledge of the (momentary) cognitive and affective load of the tasks and situation, and the capacities of the human partner (*h*Partner) to cope with this load. For adequate partnership, cognitive and affective load models are needed that support shared situation awareness, trust and scrutability. This paper presents two such models that are being developed and tested for military and space operations in situated cognitive engineering cycles.

Keywords: mental load, emotion, human-machine collaboration, synthetic or electronic partner, and cognitive engineering.

1 Introduction

Technological developments, e.g., on ambient intelligence and context-aware services, enable the design of joint cognitive systems in which the human and machine actors collaborate in an effective and efficient way. Such systems provide new possibilities to cope autonomously with unexpected, complex and potentially hazardous situations by mutual human-machine amplification of individual capabilities and by combining human and machine cognitive resources for situation assessment, problem solving and planning. Specifically, we aim at the design of a collection of distributed and connected personal, synthetic or electronic, partners (*e*Partners) to support the human partners (*h*Partners) in the military, space and medical domain. For these three domains, important goals of the partnership are, respectively, to dynamically attune the task allocation and level of automation to the available cognitive capacities and work context of operations [1], to improve human-machine team's resilience and safeguard *h*Partners from failures [2], and to improve the self-care of chronic patients [3].

1.1 *e*Partner

To establish the goals of dynamic task allocation, team resilience or patient's self-care, the *e*Partner has to acquire and maintain knowledge of the (momentary)

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cognitive and affective load of the tasks and situation, the capacities of its *h*Partner to cope with this load, and *h*Partner's intentions. In general, an *e*Partner has knowledge of its *h*Partner with respect to his or her permanent characteristics (e.g., personality), dynamic characteristics (e.g., experience), base-line state (e.g., "normal" heart rate), momentary state (e.g., current momentary heart rate), and tasks (e.g., alarm handling). Based on this knowledge, the *e*Partner maintains a model of the task demands that are critical for its *h*Partner (e.g., the risks of cognitive lock-up in complex task situations; [4]). It will have different mitigation strategies to prevent or to diminish negative effects of human operations in such critical situations by taking over some tasks, guiding the task performance, requesting other partners to help, or subtle actions to keep the human in an adequate state (e.g. open-mindedness, alertness).

The knowledge or models that *e*Partners maintain of their *h*Partners should support the sharing of knowledge and maintenance of an adequate trust level.

1.2 Shared Knowledge

The *e*Partner should be able to express and share its knowledge, and to express its capabilities to apply this knowledge for the collaborative activities. Partner's expressions of their cognitive capacities and emotions are crucial for real collaboration, for example, for effective critiquing [5] or persuasion [6]. The user interface of the *e*Partner is "natural or intuitive" by expressing and interpreting communicative acts based on a common reference of the human and machine actors.

A shared understanding of the current situation and the resources that are available for the required activities is needed for collaboration. It is important that the *h*Partner can access *e*Partner's knowledge about the situation and him or her, and that he or she has the possibility to correct or add *h*Partner's knowledge. He or she needs to know what the "*e*Partner knows about him or her", setting requirement for the scrutability of the models [7]. The humans should be able to inspect and control the details of the information held about them and the context in which they operate, the processes used to gather the information and the way that it is used. It may be possible to change some values according to his or her view (or according to the view of another partner of the team).

1.3 Trust

To really collaborate with a "knowledgeable" *e*Partner, the *h*Partner must trust it. Given the dependency of the astronauts on MECA and the ways the human-machine collaboration will be shaped, a high level of trust is required. For trust, we distinguish four dimensions: the experience, the persistence and competence of system behavior, the perceived servitude of the system, and the understanding of the system's content and operations. Trust in automation has both cognitive aspects, expressed in beliefs and expectations about the automation, as well as affective and motivational aspects, expressed in feelings and intentions toward the automation [8,9]. Sharing knowledge as described in section 1.2 is expected to support trust.

In sum, the ePartners must have knowledge of the momentary cognitive and affective load the tasks and contexts bring about for each team member. Furthermore, they should be able to communicate this knowledge with the human team members.

Therefore, we develop and apply so-called practical or "simple" theories on cognitive and affective load. Such a theory has face validity and comprises accepted features of human cognition, to be "contextualized, quantified and instantiated" for the application domain such as defense and space missions. Multimodal user-state, user-behavior and context sensing technology is used to "feed" the load models. The nest sections present two load models that are being developed and tested for military and space operations in situated cognitive engineering cycles.

2 Cognitive Task Load

Neerincx [10] developed a model of cognitive task load (CTL) and applied it for task allocation and the design of adaptive interfaces. This model could be part of the knowledge that the *e*Partner has of its *h*Partner, distinguishing three types of cognitive load factors.

First, the *e*Partner should have knowledge of the *time pressure*. In addition to the operational and contextual demands, human's cognitive processing speed determines this pressure for an important part, that is, the speed of executing elementary cognitive processes. Particularly, time pressure is high when the processes require a lot of attention and focused concentration (cf. [11]). Cognitive processing speed is determined by the individual capabilities to search and compare known visual symbols or patterns, to perform simple (decision-making) tasks, and to manipulate and deal with numbers in a fast and accurate way. Second, the *task complexity* affects the cognitive task load. Task information that is processed automatically, results into actions that are hardly cognitively demanding. Performance of routine procedures results into relatively efficient problem solving. Problem solving and action planning for relatively new situations can involve a heavy load on the limited capacity of working memory. Humans expertise and experience with the tasks have substantial effect on their performance and the amount of cognitive resources required for this performance. Higher expertise and experience result in more efficient, less-demanding deployment of the resources. Third, the CTL theory distinguishes *task switching or sharing* as a third load factor to address the demands of attention shifts or divergences. Complex task situations consist of several different tasks, with different goals. These tasks appeal to different sources of human knowledge and capacities and refer to different objects in the environment. Switching entails a change of applicable task knowledge.

The effects of cognitive task load depend on the concerning task duration (Table 1) In general, the negative effects of under- and overload increase over time. Under-load will only appear after a certain work period, whereas (momentary) overload can appear at every moment. When task load remains high for a longer period, carry-over effects can appear reducing the available resources or capacities for the required human information processing. Vigilance is a well-known problematic task for operators in which the problems increase in time. It can result in either stress due to the requirement to continuously pay attention on the task or boredom that appears with highly repetitive, homogeneous stimuli.

Table 1. Overview of 4 negative effects of cognitive task demands for a certain task period

	Task Performance Period		
	Short (<5min)	Medium (5-20min)	Long (>20min)
Time pressure *Low* Complexity *Low* Task switches *Low*	no problem	Under-load	
Time pressure *High* Complexity *Low* Task switches *Low*	no problem		Vigilance
Time pressure *High* Complexity *All* Task switches *High*	Cognitive lock-up		
Time pressure *High* Complexity *High* Task switches *High*	Overload		

3 Affective Load

Affection, emotion and mood are concepts that can have many interpretations. We will use affection and emotion interchangeably to reflect a momentary state, and mood to describe a can last for a state with a longer duration. Affection comprises a broad range of feelings that humans can have and which can influence humans in their behavior [12]. For characterizing the affective load, we focus on the underlying, often physiologically correlated factors (e.g. arousal) and map these onto distinct dimensions. Such dimensional models are helpful in both recognition and expression, as well as in models of emotion generation, in situations where sufficient data may not be available for more highly differentiated responses. Based on the Pleasure-Arousal-Dominance (PAD) model of Mehrabian, we distinguish two dimensions to

Table 2. The 2D model of affection or emotion with example effects

		Valence	
		NEGATIVE	**POSITIVE**
Arousal	**HIGH**	tunnel vision and higher concentration	divergent and creative thinking and problem solving
	LOW	boredom	relaxation

define the emotional state: the arousal level—low versus high—and the valence—positive versus negative (table 2). We do not distinguish a separate dominance dimension like the original PAD-model, because the dominance scale proved to explain the least variance and had the highest variability in terms of its inferred meaning in previous research.

Emotions can be measured through different modalities. Usually, physiological measures such as heart rate or skin conductivity are considered obtrusive, while speech and facial expressions are relatively non-obtrusive measures.

4 Cognitive Engineering for H-M Partnership

Due to the adaptive nature of both the human and machine behavior, it is difficult to provide generic and detailed predictions on the overall human-machine performance. Therefore, Neerincx & Lindenberg developed a situated cognitive engineering method [13]. First, the technological design space sets a focus in the process of specification and generation of ideas. Second, the reciprocal effects of technology and human factors are made explicit and are integrated in the development process. As shown in the previous sections, the human factors knowledge provides relevant theories, guidelines, support concepts and methods for the specification and assessment of H-M partnerships. In the specification, both the guidelines and the technological design space must be addressed concurrently. In the assessment it is checked whether the specifications agree with these guidelines and the technological design space.

Furthermore, the practical theories of cognitive and affective are being refined, situated and validated in the domain of application. For realizing adequate H-M partnership, generic human-factors knowledge and *e*Partner concepts are refined, contextualized and tested within the domain. The situated cognitive engineering framework has been developed and applied in the defense, space and medical domain to enhance the capacities of teams and team-members during critical and complex tasks (e.g., to improve task load management, trouble-shooting and situation awareness).

For example, for future manned space missions to the Moon or Mars, we specified a number of partnership scenarios. One scenario starts with two human-machine teams, team A and B, exploring the surface at different locations. Team B is working at a large distance from the habitat, and has a relatively large rover that can carry an astronaut. At the habitat, one astronaut is doing her exercises following her ‘self-care program’. For one member of team A, Charles, the spacesuit heater fails (figure 1). Team A, i.e. consisting of *e*Partners and astronauts, starts a fault detection and diagnosis process. The *e*Partner detects the *affective state* “panic”, predicts hypothermia and calls for help. In parallel, the following actions are started:

- Habitat prepares to receive astronaut (goal resetting)
- *e*Partner starts rescheduling the activities of actors, based on current *cognitive task load* states
- Rover in other team offers help & starts out
- *e*Partner informs astronaut (& others) of plan
- Astronaut faints earlier than predicted
- *e*Partner & rover devise way to pick up astronaut
- Rover transports astronaut to habitat

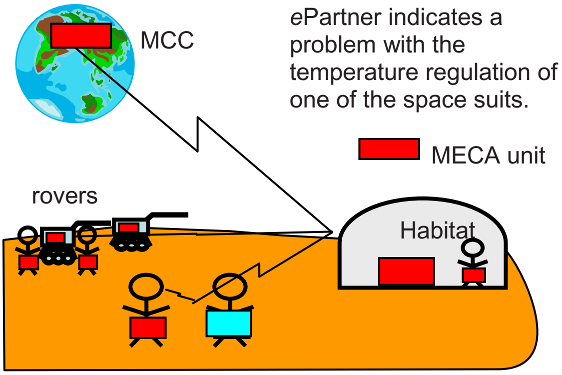

Fig. 1. Example scenario state for the suit failure (MCC = Mission Control Center)

Note that the focus is on the performance of the mental activities of human actors and the cognitive functions of machine actors, to achieve the (joint) operational goals. In this way, the notion of collaboration has been extended, viewing the machine as a social actor that can take initiative to act, critique or confirm in joint human-machine activities. The design focuses on the manifestation of these activities in "real settings", corresponding to the concept of macrocognition [14]. The cognitive engineering method is based on experiences with previous and current task performances (space, navy, care sector) and based on practical theories as described above.

5 Conclusions

We are developing models for hybrid human-machine systems that can cope autonomously with unexpected, complex and potentially hazardous situations. The synthetic or electronic partner (*e*Partner) has to acquire and maintain knowledge of the (momentary) cognitive and affective load of the tasks and situation, and the capacities of the human partner (*h*Partner) to cope with this load. For adequate partnership, cognitive and affective load models are needed that support the sharing of knowledge and acquisition of adequate trust levels. This paper presented two such models that are being developed and tested for military, space and medical operations, the models for cognitive and affective load. Test results are being used to improve the models and to implement them into *e*Partners.

Building an automatic cognitive and affective load recognition system can be very complex, especially if we want to incorporate an accurate and complete model or theory of cognition or affection. However, it may not always be necessary or realistic to pursue an ideal model; detection of 'simple' striking load states in context (e.g., 'panic') can also be of high practical value to realize effective partnership.

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