Towards Task Allocation Decision Support by means of Cognitive Modeling of Trust

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Abstract. An important issue in research on human-machine cooperation concerns how tasks should be dynamically allocated within a human-machine team in order to improve team performance. The ability to support humans in task allocation decision making requires a thorough understanding of its underlying cognitive processes, and that of relative trust more specifically. This paper presents a computational agent-based model of these cognitive processes and proposes an experiment design that can be used to validate theoretical aspects of this model.

1 Introduction

The increasing intelligence of machines leads to a shift from HCI to human-machine *cooperation* research [1]. Problems arise when small human-machine teams try to cooperate on a cognitive level. A goal in human-machine cooperation research is to solve these problems. Optimizing performance of the human-machine team is not likely to be gained by improving human-alone or machine-alone performances. It is important that cooperative tasks within the team, and more specifically the dynamic allocation of tasks, are improved as well. This requires an understanding of the cognitive processes underlying taskallocation decisions. A useful cognitive theory of task allocation decision making should represent those attributes and their relations that are considered in making decisions on task allocation. A validated model can subsequently be used by decision support systems to support 1) the acquisition of information concerning these attributes, 2) the analysis and integration of this information, 3) the selection of appropriate changes in task allocation, and 4) the execution of these actions [2].

Although there has recently been an increase in human factors research concerning trust and automation reliance [3–8], few attempts have been undertaken to formalize the cognitive processes underlying task allocation decisions [9, 10]. Therefore more research on its theoretical framework is needed. In the AI and sociology community research on the formalization of trust and delegation decisions is present, e.g. [11, 12], but not specifically with respect to dynamic decision making in human-machine cooperation.

The present research attempts to bridge this gap between human factors and AI research by developing a computational model of task allocation decision making that can be used in further understanding and supporting human-machine cooperation. It is work in progress. First, the theoretical aspects of task allocation decision making are introduced. Second, a formal cognitive model is defined. And third, based on this model, an experimental environment is described that can be used to validate the theoretical aspects.

2 Cognitive theory

As in [11], in this paper the term *trust* is used to refer to a mental state, a belief of a cognitive agent i about the achievement of a desired goal through another agent j or through agent i itself. In trusting agent j, agent i has, to some level, a positive expectation that agent j's actions will achieve the goal that agent i desires. Agent i's expectation of j's performance is calibrated by direct experience with j's performance. Trust is dynamic, but it does not simply increase and decrease with positive and negative experiences. How trust changes by successes and failures, for one, depends on how increases and decreases in performance are interpreted and causally attributed [13, 4]. Trust is more than other concepts subject to error. One type of error is that humans tend to overestimate their own performance. Humans, for instance overestimate the number of tasks they can complete in a given period of time [14]. Another type of error occurs when humans form expectations about the performance of automation. It is found, for instance, that humans have a bias toward automation [15, 16].

There are also indirect sources of knowledge about performance. Reputation and gossip, for instance, enable agents to develop trust without any direct experience. In the context of trust in automation, response times to warnings tend to increase when false alarms occur. This effect was counteracted by gossip that suggested that the rate of false alarms was lower than it actually was [17]. Trust can also be based on analogical judgments, i.e. judgment about the trustworthiness of a category rather than on the actual performance of one of it's presumed members. Although not always recognized by analytical approaches to trust, it should be noted that humans are cognitive misers and try to save the effort that is required in deliberation. In naturalistic setting it is observed that decision makers seldom engage in extensive information acquisition, conscious calculations or in an exhaustive comparison of alternatives [18]. In these multi-tasking environments automatic processes play a substantial role in attributional activities, with many aspects of causal reasoning occurring outside conscious awareness. In [19] for instance it is suggested that computer etiquette may have an important influence on human-machine cooperation. Etiquette may influence trust because category membership associated with adherence to a particular etiquette helps people to infer how automation will perform.

Many theories in the human factors literature about the cognitive processes underlying task allocation decisions include a notion of relative trust, i.e. differences of trust in two agents. Empirical results from human factors experiments show that as the trust in machine performance is significantly higher than trust in own performance, humans intend to allocate tasks to the machine, and when the reverse is true, humans prefer to allocate tasks to themselves [5, 20–22]. Theories on these results describe factors that affect trust in machine performance, such as machine performance reliability and error costs. Factors that affect trust in own performance are for instance task difficulty, skill, cognitive biases and the effects of social and motivational processes [21].

Trust is distinguished from the decision to allocate a task to an agent or rely on an agent. The term *task allocation decision* is used to refer to the decision to rely on an agent's goal-directed actions to achieve a desired goal. One might argue that an agent is more likely to rely on another agent when its workload is high compared to when it is moderate or low. In [7], however, it is pointed out that the relation between workload and the reliance decision has not been empirically validated and it is suggested that this relation is obscured by individual differences. In [23] it is shown that humans do not simply allocate tasks to automation so as to free up mental resources for concurrent tasks. It has been hypothesized that reliance decisions are not only influenced by individual differences, such as skill on the task or costs of delaying concurrent tasks, but also by the effort or time needed to engage automation. It is expected that the influence of the effort or time for the actual allocation of tasks will be particularly evident when the workload of the agent is already high.

The task allocation decision is also bounded by a certain inhibitory bound or allocation preference threshold [20]. This threshold determines when relative trust does not result in a preference difference high enough to rely on an agent. Theory development on these factors is immature, but it is expected that the height of the threshold will be influenced by the difference between the trust uncertainty and the urgency and importance of the task allocation.

Finally, the task allocation decision is distinguished from the goal-directed actions of allocating a task or actually relying on an agent. The term *task allocation* is used to refer to the overt behaviors of agent i that are required to actually rely on agent j. The decision to rely on agent j may not be sufficient to reach the state in which the task is actually allocated to agent j. There may be unanticipated obstacles interfacing i and j that hinder the actual allocation of a task. This refers to the ability of the agent and opportunity in the environment. Furthermore, there can also be an action to allocate a task to an agent without a decision to allocate this task. This can be the case for instance when execution errors are made.

3 Formal cognitive model

Suppose a decision maker is given a (meta) task τ_m for which it has to make a best choice in allocating a certain (object) task τ_o to either a human agent H or a machine agent M. The *Decision Field Theory* (DFT) is a mathematical framework for describing the dynamics of such choices [24]. In this section a formal model of task allocation decisions inspired on DFT is shown, which is used in describing the dynamics of the proposed experiment in Section 4.

The following formal model is described by means of four definitions, that is, of the *task execution state*, *trust state*, *allocation preference state*, and *preferred task execution state*. These are called states because they are time-dependent. The (preferred) task execution states are strings (sequences of characters). The trust and allocation preference states are real values.

Definition 1 (task execution state). *Let* σ_i *be a* task execution state*:*

$$\sigma_i(j, \tau_o, t_n) = APPEND_{k=0}^{n} s_i(j, \tau_o, t_k) \tag{1}$$

where $i, j \in Agents = \{H, M, *\}$*,* $\tau_o \in Tasks$ *and* s_i *is a recall function where* $s_i : Agents \times Tasks \times Time \to Actions$*, according to agent* i*. Agent* $*$ *represents the infallible agent. The function* σ_i *thus returns a string of sequentially ordered actions resulting from the execution of task* τ_o *by agent* j *according to agent* i *until time point* t_n*. Note that* $\sigma_i(*, \tau_o, t)$ *indicates the task execution state of the infallible agent* according to agent i*. The function* $APPEND$ *appends an action at the tail of a given string.*

Example 1. An example of an task execution state $\sigma_H(H, \tau_o, t_3) =$ "$\alpha_1\alpha_3\alpha_2\alpha_4$", where $\alpha_1, \alpha_3, \alpha_2, \alpha_4 \in Actions$ are executed actions at time points t_0, t_1, t_2, and t_3, respectively, and $H \in Agents$.

The recall function s_i might result in actions falsely identified by agent i as executed on a certain time point by a certain agent. Such errors can be modeled by means of decays, e.g. by using a time-dependent randomization function. This means that $\sigma_i(j, \tau, t_n)$ is not necessarily the first part of $\sigma_i(j, \tau, t_m)$ for $t_n \leq t_m$ and arbitrary j (including $j = *$) and τ. In contrast, for $i = *$ the latter is not the case, which in other words means that the infallible agent has no regrets.

Similar to [25], trust is considered a mental agent concept that depends on the past experiences that coincide on discrete time points with events that affect the agent's trust state. In this paper experiences are given by evaluating task execution states of an agent by means of comparison with those of the supposed infallible agent. This idea of the infallible agent and the comparison may be different for each agent.

Definition 2 (trust state). *Let* T_i *be a* trust state*:*

$$T_i(j, \tau_o, t) = 1 - \frac{D_i(\sigma_i(j, \tau_o, t), \sigma_i(*, \tau_o, t))}{\mid \sigma_i(*, \tau_o, t) \mid} \tag{2}$$

where D_i *is a function calculating the distance between two strings according to agent* i*. Trust states based on trust states with length* 0*, i.e. when* $\mid \sigma_i(*, \tau_o, t) \mid = 0$*, have initial values. Furthermore,* $D_i(\sigma_i(j, \tau_o, t), \sigma_i(*, \tau_o, t))$ *is also written as the error rate* $e_i(j, \tau_o, t)$*.*

The distance function D_i can be a *form* of the Hamming Distance (HD), i.e. for trust calculation based on real performance history by means of 1-to-1 distance, or for instance the Levenstein Distance (LD), i.e. for determining model validity by means of the calculation of basic edit distance. The remaining of D_i is determined by agent i's interpretation and causal attribution resulting in inflation of penalties on errors due to for instance the workload and resource boundedness of agent j, complexity of τ_o, and memory decay, at time points $t_k \leq t$, or even $t_k > t$ when future events are anticipated in these terms. Three cases of memory decay are for instance modeled in [25]. Initial values of trust states, when $\mid \sigma_i(*, \tau_o, t) \mid = 0$, are determined by only such indirect indicators. Furthermore, all agents but $*$ can make errors or are biased in distance calculation, as in mistaken memory recalls and prejudices, respectively.

Example 2. Please recall Example 1 of agent H. Let $\sigma_H(*, \tau_o, t_3) = "\alpha_1\alpha_2\alpha_3\alpha_4"$. Let's assume that exactly $D_{H,1} = HD$ is used. This means that trust state $T_H(H, \tau_o, t_3) = 1 - \frac{2}{4} = \frac{1}{2}$. But if we assume that exactly $D_{H,2} = LD$ is used, then the trust state $T_H(H, \tau_o, t_3) = 1 - \frac{1}{4} = \frac{3}{4}$. In this case always holds that $D_{H,2} \leq D_{H,1}$.

Task allocation decisions are based on allocation preferences. As is proposed in [8, 22] the following model assumes that preferences are determined by trust in the self, trust in the other, and a certain corresponding inhibitory bound or allocation preference threshold.

Definition 3 (allocation preference state). *Let P_i be an* allocation preference state*:*

$$P_i(\tau_o, t) = T_i(j, \tau_o, t) - T_i(i, \tau_o, t) \tag{3}$$

where the trust state $T_i(j, \tau_o, t)$ means that agent i trusts agent j with respect to its performance in executing task τ_o at time point t. Agent i prefers allocation of τ_o to j iff $1 \geq P_i(\tau_o, t) > \theta_i(\tau_o, t)$ and to i iff $-1 \leq P_i(\tau_o, t) < -\theta_i(\tau_o, t)$ at time point t. The function θ_i represents the inhibitory bound of agent i. In other words, positive values for P_i indicate the tendency to allocate to the other and negative values to itself, if it exceeds a certain threshold $(-)\theta_i$. The real interval $[-\theta_i, \theta_i]$ indicates indifference of the agent i with respect to its allocation preference. The value of $\theta_i(\tau_o, t)$ depends on the characteristics of its parameters, such as decay due to costs of waiting [26].

Example 3. Please recall Example 2 of agent H. Suppose that $D_H = HD$, that $\sigma_H(M, \tau_o, t_3) = "\alpha_2\alpha_2\alpha_3\alpha_4"$, and thus $T_H(M, \tau_o, t_3) = \frac{3}{4}$, for another agent $M \in Agents$. This means that the allocation preference state $P_H(\tau_o, t_3) = \frac{3}{4} - \frac{1}{2} = \frac{1}{4}$. Hence, if $\theta_H(\tau_o, t_3) < \frac{1}{4}$, then at time point t_3 agent H prefers the allocation of task τ_o to agent M.

The above does not yet take into account that task allocation decisions also concern the effort or time needed for engaging (re)allocation and all other consequences afterwards, such as task switching costs relating other tasks and additional overhead (like in [1]). In fact, this may result in the opposite of what one might expect from mere difference in trust states. This thus suggests a different view of relative trust, namely trust relating the differences in desirability of the resulting outcome of *commencing* the allocation of a certain task to a certain agent, with respect to the overall system performance. In the context of the experiment proposed in the next section initially the first definition is chosen.

The allocation task τ_m itself can result in a task execution state $\sigma_i(j, \tau_m, t)$, trust state $T_i(j, \tau_m, t)$, and allocation preference state $P_i(\tau_m, t)$ with its inhibitory bound $\theta_i(\tau_m, t)$ for $i, j \in Agents$ by means of Equations 1, 2, and 3, respectively. In other words, this enables a decision maker to make preferred decisions on the allocation of the allocation task.

Definition 4 (preferred task execution state). *Let π_i be a* preferred task execution state*:*

$$\pi_i(\tau_o, t_n) = APPEND_{k=0}^{n} s_i(j, \tau_o, t_k) \tag{4}$$

where each agent $j \in Agents \setminus \{*\}$ is preferred at time point t_k by the preferred allocator determined by $\pi(\tau_m, t_n)$ according to agent $i \in Agents$.

Example 4. Please recall Example 3 of agent H. Suppose that task τ_m is allocated to agent H. In this case the preferred task execution state $\pi_H(\tau_o, t_3) =$ "$\alpha_1\alpha_3\alpha_3\alpha_4$", because of allocation preference states indicating the preferred allocation of task τ_o to agent H, H, M, and M, at time points t_0, t_1, t_2, and t_3, respectively. This might be different if task τ_m is allocated to agent M at a certain time point, possibly due to differences in states, inhibitory bounds, recall, and distance functions.

Finally, true states are subscripted with a $*$, i.e. states according to the infallible agent; e.g., $\pi_*(\tau_o, t)$ denotes the actual preferred task execution state. Performance of a cooperative MAS is therefore calculated by means of $HD(\pi_*(\tau_o, t), \sigma_*(*, \tau_o, t))$.

4 Experiment design

In order to validate implications of the theory introduced in Section 2 a simple experimental task is developed. The goal of this experimental task is to predict, as a human-machine team, the location of a disturbance. In every trial the disturbance can occur at one of three locations. Also each trial consists of three phases: a prediction phase, a selection phase, and an update phase. The human and the machine are both required to execute three tasks ($\tau_{o,m,u}$), one for each of these phases. The first task is to decide on the location of the next disturbance based on an internal prediction model. This decision is retrieved by letting both indicate a specific button. Given both predictions, the next task is to let them decide on which advise to trust the most based on their internal selection model.[3] This is again retrieved by letting both indicate a specific button, either following the prediction of itself, the other, both, or nobody. In the last phase the location

[3] This task is actually not a task allocation decision task in the precise sense of the definition given in Section 2. It is meant to catch an important prerequisite for the allocation decision, namely reasoning with allocation preference states.

of the disturbance is revealed according to a predetermined string $\sigma_*(*, \tau_o, t)$, which both agents are required to process by means of updating their internal models for task τ_o and τ_m. In Figure 1 the interface of a first implementation of the experimental environment is shown.

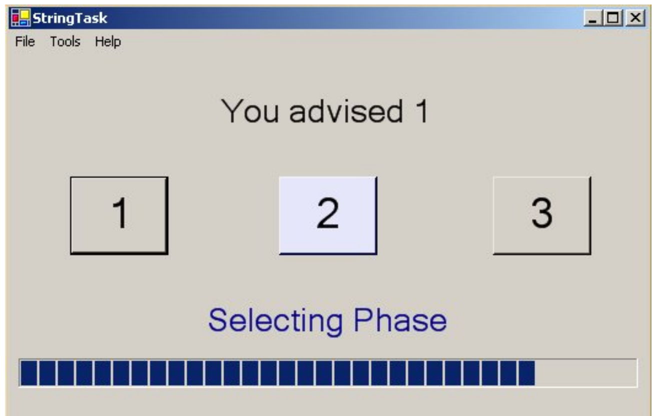

Fig. 1. The interface of a first implementation of the experimental environment StringTask. A selection phase is shown, where the human predicted location 1 and the machine location 2. The allocator should indicate which button to select, based on both predictions and its internal selection model. After this the update phase indicates its soundness, which is used for updating the internal models.

The independent variables are the error rates of the machine for each task, and the difficulty of the string. The error rate of the machine $e_*(M, \tau, t)$ is manipulated by having it choose $e_*(M, \tau, t) \cdot \mid \sigma_*(M, \tau, t) \mid$ times a random action in stead of the action $s_M(M, \tau, t)$, for each task τ and time point t. The difficulty of the string is manipulated by changing its length and generation rules, which has been subject in the study of human sequential processing some decades ago (e.g., [27]).

The measured dependent variables are human-machine system performance and the error rates of the human for each task. These are simply calculated by means of the HDs of the preferred task execution state $\pi(\tau, t)$ and task execution state $\sigma_*(H, \tau, t)$, respectively, with the infallible task execution state $\sigma_*(*, \tau, t)$, for each task τ and time point t.

In the following experiment the effort and time to engage (re)allocation is kept the same for both human and machine. In order to ascertain that the experimental task can be reliably used to validate implications of the theory two straightforward hypotheses should hold:

– At each moment the participant prefers allocation of a task to the machine instead of to himself (or herself) when his trust in his own performance is expected to be significantly lower compared to his trust in the performance of the machine.

– At each moment the participant prefers allocation of a task to himself instead of to the machine when his trust in the performance of the machine is expected to be significantly lower compared to his trust in his own performance.

To validate the first hypothesis, the trust state $T_H(H, \tau_o, t)$ is experimentally manipulated by varying the error rate $e_H(H, \tau_o, t)$. This is done by decreasing the complexity of the string. If error rate $e_*(M, \tau_o, t)$ remains low enough, this ought to result in an allocation of the task τ_o to agent M by agent H, due to $1 \geq P_H(\tau_o, t) > \theta_H(\tau_o, t)$. In this experiment the task can be executed in three levels of difficulty. The level of difficulty is manipulated by increasing the memory-load of the internal prediction model that the agent H needs to use for executing task τ_o. It is known that human working memory has a limited capacity and that performance errors will result when more capacity is demanded by the task than can be supplied by the human. The memory-load of the internal models is manipulated by increasing the difficulty of the string.

Validation of the second hypothesis is symmetric. Trust in machine performance is manipulated by varying machine reliability. In this experiment agent M will perform the task at a reliability of 100, 70 and 50% independently of the difficulty of the task for agent H. In prior research it is often found that reliability lower than 70% will result in disuse of automation [20]. The above manipulations result in a 3 (difficulty) × 3 (reliability) experiment design as shown in Figure 2.

SD × MR	SD1	SD2	SD3
100% MR	$-\theta_H \leq P_H \leq \theta_H$	$1 \geq P_H > \theta_H$	$1 \geq P_H > \theta_H$
70% MR	$-1 \leq P_H < -\theta_H$	$-\theta_H \leq P_H \leq \theta_H$	$1 \geq P_H > \theta_H$
50% MR	$-1 \leq P_H < -\theta_H$	$-1 \leq P_H < -\theta_H$	$-\theta_H \leq P_H \leq \theta_H$

Fig. 2. The proposed 3 (string difficulty) × 3 (machine reliability) experiment design with the expected properties of corresponding allocation preference state P_H.

It is expected that higher θ_H values will result in higher error rates $e_*(H, \tau_m, t)$ in the selection task due to unwanted indifference. Undoubtedly decision support is needed when in this diagonal region. How to support this and other results of this experiment will be subject of further experimental research.

5 Discussion

In this paper a computational model of trust based task allocation decision making and an experiment design used for theory validation are proposed. Though task allocation decision support by means of cognitive modeling of trust is clearly relevant, it is a field in AI that is quite new.

The present research is work in progress. After being confident on the replicability of previously found experimental findings in various domains in literature

[5, 20–22] by means of validating the two above mentioned hypotheses, the experimental environment will be used for further research, such as on indirect acquisition of knowledge (e.g., reputation, gossip), analogical judgments, allocation engagement costs (e.g., waiting, cooperation, and overhead costs), allocation implementation errors, level of autonomy, the allocation decision inhibitory bound, quantity and seriality of tasks, and time pressure. Extensions of (agent-based) cognitive models of trust and invocation concepts for machine monitoring of the allocation task (adaptive systems) are subject of investigation in the near future. Future research on cognitive modeling of trust aims at support in the four stages of information processing deliberation [2]: the acquisition of information relevant for trust, its integration to trust concepts, task allocation decision making based on trust concepts, and the implementation of the allocation decision. Moreover, future research focusses on investigating the degree to which new or extended cognitive theories, based on formal modeling and controlled laboratory experiments, are translatable to more complex real world situations.

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