Human-Robot Collaboration

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ABSTRACT

We have conducted a user study to investigate the importance of emotional awareness and the underlying affect-driven processes during a human-robot collaboration. The goal of this user study was twofold: (1) Investigating the overall functionality of the major mechanisms and the underlying algorithms in our architecture, (2) Evaluating human's willingness and assessment of collaboration with an emotion-aware and an emotion-ignorant robot. We designed a simple table top game to simulate the collaborative environment in which a participant and the robot were "installing" a solar panel together. The result of our user study shows a significant difference between humans' preference of working with an emotion-aware robot during collaboration.

CCS Concepts

•**Computer systems organization** → **Embedded systems;** *Redundancy;* Robotics; •**Networks** → Network reliability;

Keywords

Human-Robot Collaboration, Affect-Driven Processes, Emotion-Awareness

1. INTRODUCTION

The idea of robots or other intelligent agents living in a human environment has been a persistent dream from science fiction books to artificial intelligence and robotic laboratories. Collaborative robots are expected to become an integral part of humans' environment to accomplish their industrial and household tasks. In these environments, humans will be involved in robots' operations and decision-making processes. The involvement of humans influences the efficiency of robots' interaction and performance, and makes the robots sensitive to humans' cognitive abilities and behaviors.

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This work is implemented as part of a larger effort to build robots capable of generating and recognizing emotions in order to be better collaborators. In this paper, we report on the specific problem of appraising the relevance and controllability of events within a collaborative interaction. Our contribution is to ground general appraisal concepts in the specific context and structure of collaboration. This work is part of the development of *Affective Motivational Collaboration Theory* which is built on the foundations of the *SharedPlans* theory of collaboration [5] and the *cognitive appraisal* theory of emotions [4].

There are several appraisal models (e.g., EMA [9]) contributing in different applications such as social sciences, virtual agents, and robotics. However, none of these models have focused on the appraisal processes during collaboration. We believe appraisal plays a key role in collaboration due to its regulatory and evaluative nature. Also, collaboration induces some changes to underlying appraisal processes due to its unique nature. For instance, although the appraisal models mostly use utility to compute the relevance of an event, we have found new cognitive components involved in determining utility because of the influence of the collaboration. These components, such as the recurrence of a belief by the human collaborator or the influence of the human collaborator's perceived emotion on the robot's decisions emphasize the fact that collaboration requires different procedures in appraisal processes. In this paper, we provide the relevance and controllability appraisals of an event in the collaboration context.

2. RELATED WORK

Our work builds on the general notions of appraisal theory [4, 10, 14, 15], but is focused on its application in human-robot collaboration. Computational appraisal models have been applied to a variety of uses in psychology, robotics, AI, and cognitive science. For instance, in [9] EMA is used to generate specific predictions about how human subjects will appraise and cope with emotional situations. Furthermore, appraisal theory has been used in robots' decision making [3], or in their cognitive systems [6, 7]. In the virtual agents community, empathy and affective decision-making is a research topic that has received much attention in the last two decades [11, 12, 13, 17]. However, EMA and other work in artificial intelligence and robotics which apply appraisal theory do not focus on the dynamics of collaborative contexts [1, 8, 9, **?**].

The computational collaboration model in our work is strongly influenced by the SharedPlans theory [5]. However, our algorithms are also compatible with other collaboration theories, e.g., Joint

Figure 1: A sample black and white graphic.

Figure 2: A sample black and white graphic that has been resized with the `includegraphics` command.

Intentions theory [2], or STEAM [16]. These theories have been extensively used to examine and describe teamwork and collaboration. Yet, collaboration and emotion theories have never been combined, as they are in our work. We believe a systematic integration of collaboration theories and appraisal theory can help explain the underlying processes of collaboration structure.

3. AFFECTIVE MOTIVATIONAL COLLABORATION THEORY

Affective Motivational Collaboration Theory deals with the interpretation and prediction of observable behaviors in a dyadic collaboration [**?**]. The theory focuses on the processes regulated by emotional states. The observable behaviors represent the outcome of reactive and deliberative processes related to the interpretation of the self's relationship to the environment. Affective Motivational Collaboration Theory aims to explain both rapid emotional reactions to events as well as slower, more deliberative responses. The reactive and deliberative processes are triggered by two types of events: *external* events, such as the other's *utterances* and *primitive actions*, and *internal* events, comprising changes in the self's mental states, such as belief formation and emotional changes. The theory explains how emotions regulate the underlying processes when these events occur. It also elucidates the role of *motives* as goal-driven emotion-regulated constructs with which a robot can form new intentions to cope with events.

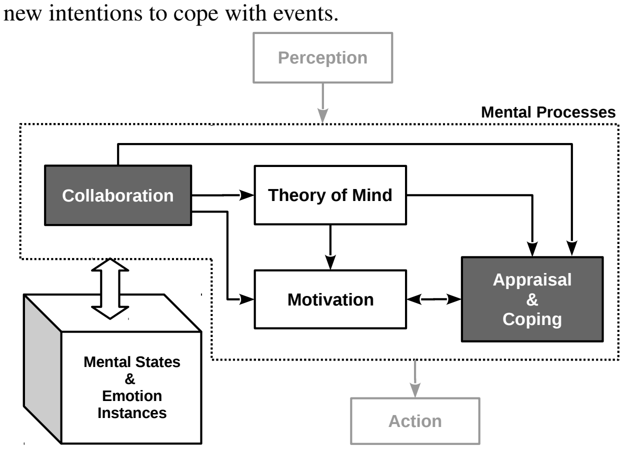

Figure 3: Computational framework based on Affective Motivational Collaboration Theory (arrows indicate primary influences between mechanisms).

Our focus is on the mechanisms depicted as mental processes in Figure 3 along with the mental states. Each mechanism includes one or more processes in our architecture. For instance, the *Collaboration* mechanism includes processes such as *Focus Shifting* and *Constraint Management*, while as we discuss in Section **??** the *Appraisal* mechanism includes processes to compute the values for different appraisal variables. The *mental states* includes self's (robot's) beliefs, intentions, motives, goals and emotion instances as well as the anticipated mental states of the other (human). The *Collaboration* mechanism maintains constraints on actions, including task states and the ordering of tasks, and provides processes to update and monitor the shared plan. The *Appraisal* mechanism is responsible for evaluating changes in the self's mental states, the anticipated mental states of the other, and the state of the collaboration environment. The *Coping* mechanism provides the self with different coping strategies associated with changes in the self's mental states with respect to the state of the collaboration. The *Motivation* mechanism operates whenever the self a) requires a new motive to overcome an internal impasse in an ongoing task, or b) wants to provide an external motive to the other when the other faces a problem in a task. The *Theory of Mind* mechanism infers a model of the other's anticipated mental state. The self progressively updates this model during the collaboration.

3.1 Mental States

A brief description of mental states is provided as prerequisite knowledge for understanding the appraisal processes. The mental states shown in Figure 3 comprise the knowledge base required for all the mechanisms in the overall model. Mental states are conscious states of mind providing the content for cognitive processes. These mental states possess attributes, each of which provides a unique interpretation of the related cognitive entities. The self uses these attributes whenever there is an arbitration in the internal cognitive processes. We only describe some of the attributes of beliefs and motives in this paper, since they are used in our appraisal algorithms.

Beliefs are a crucial part of the mental states. Beliefs have attributes and they impact different processes of the framework such as the evaluation of an external event by the Appraisal mechanism, and updates to the collaboration plan. We use three belief attributes in the Appraisal mechanism. Belief *strength* is about how strongly the self holds salient beliefs about an object, an entity, or an anticipated behavior. The *saliency* of a belief is a cognitive attribute that pertains to how easily the self becomes aware of a belief. The *persistence* of a belief refers to how resistant the belief is to changes.

Motives are mental constructs which can initiate, direct and maintain goal-directed behaviors. They are created by the emotion-regulated Motivation mechanism. Motives can cause the formation of a new intention for the robot according to: a) its own emotional states, b) its own private goal, c) the collaboration (shared) goal, and d) other's anticipated beliefs. Motives possess a set of attributes. The Motivation mechanism compares motives based on the quality of these attributes and chooses the one which is the most related to the current state of the collaboration. We use two motive attributes in Appraisal mechanisms. The *importance* of a motive is determined by the corresponding beliefs about the effects of achieving or not achieving the associated goal. The *urgency* of a motive defines how much time the self has to acknowledge and address that motive before it is too late.

Intentions are mental constructs directed at goals and future actions. They play an essential role in taking actions according to the collaboration plan as well as behavior selection in the Coping mechanism. Intentions are also involved in selecting intention-related strategies, e.g., planning, seeking instrumental support and procrastination.

Goals help the robot to create and update its collaboration plan according to the current private and shared goal content and structure. Goals direct the formation of intentions to take appropriate corresponding actions during collaboration.

Emotions in mental states are emotion instances that are elicited by the Appraisal mechanism, e.g., *Joy, Anger, Hope, Worry*. These emotion instances include the robot's own emotions as well as the anticipated emotions of the other which are created with the help of the processes in the Theory of Mind mechanism.

Table 1: Some Typical Commands

Command	A Number	Comments
`\alignauthor`	100	Author alignment
`\numberofauthors`	200	Author enumeration
`\table`	300	For tables
`\table*`	400	For wider tables

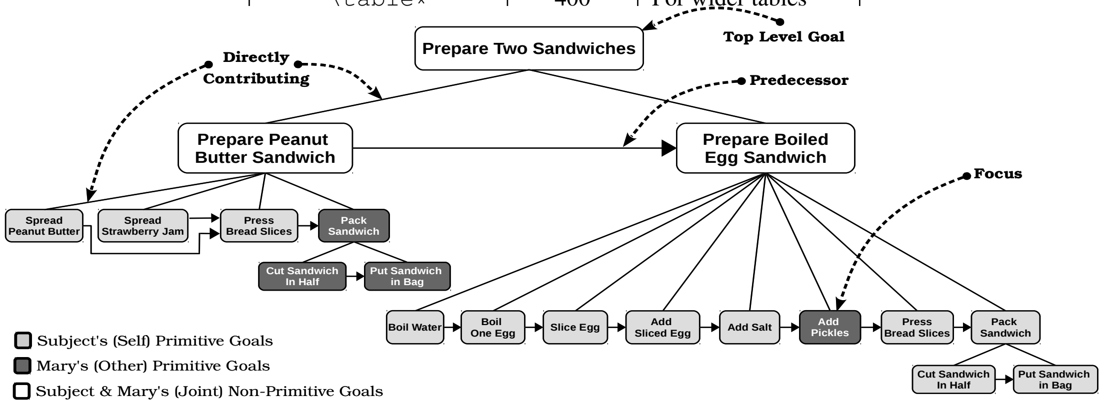

Figure 4: Example of collaboration structure (also used as task model for the evaluation).

4. COLLABORATION

The Collaboration mechanism constructs a hierarchy of goals associated with tasks in a hierarchical task network (see Figure 4), and also maintains the constraints and other required details of the collaboration including the inputs and outputs of individual tasks, the *preconditions* (specifying whether it is appropriate to perform a task), and the *postconditions* (specifying whether a just-completed task was successful). Collaboration also monitors the focus of attention, which determines the salient objects, properties and relations at each point, and shifts the focus of attention during the interaction.

Here, we describe the methods which retrieve information about the collaboration structure, and are used to compute the values of appraisal variables. In these methods, ε_t is the event corresponding to time *t*, and g_t is a given goal at time *t*.

- *recognizeGoal(ε_t)* returns the unique goal to which the given event (action, utterance, or emotional expression) directly contributes; it is only one goal since the robot can only do one primitive action at a time in our collaboration model, i.e, in the goal tree, a given primitive action can only directly contribute to one parent goal. The method returns *ambiguous* if it does not recognize a goal in the plan[1].
- *getGoalStatus(g_t)* returns whether g_t's status is ACHIEVED, FAILED, BLOCKED, INAPPLICABLE, PENDING, or IN PROGRESS. In our example, "Add Pickles" is the current (focused) goal and it is PENDING, and the "Prepare Boiled Egg Sandwich" and "Prepare Two Sandwiches" are IN PROGRESS. The focused goal is the goal that the robot currently pursues.
- *precondStatus(g_t)* returns the status of the g_t's precondition, i.e., whether it is SATISFIED, UNSATISFIED or UNKNOWN. For instance, the precondition for "Slice Egg" can indicate whether the eggs are boiled appropriately, i.e., SATISFIED.
- *isLive(g_t)* returns *true* if all the predecessors of g_t are ACHIEVED and all the preconditions are SATISFIED, i.e., PENDING or IN PROGRESS goals; otherwise returns *false*.
- *getContributingGoals(g_t)* returns g_t's children.
- *getPredecessors(g_t)* returns g_t's predecessors.
- *getInputs(g_t)* returns all required inputs for g_t. For example, the goal "Boil Water" requires inputs such as *Pot* and *Stove* (details not shown in Figure 4).
- *isAvailable(g_t, i_k)* returns whether the given input (i_k) is available for g_t. For instance, whether the *Pot* is available for the goal "Boil Water".
- *isFocused(g_t)* returns whether the focus is on g_t.
- *getResponsible(g_t)* returns responsible agent(s) for g_t. In a dyadic collaboration, both of the agents (joint) can be partly responsible for a nonprimitive goal, while each (self or other) is responsible for one or more primitive goals. For instance, both Mary and the subject are responsible for the nonprimitive goal "Prepare Boiled Egg Sandwich", whereas only Mary is responsible for the primitive goal "Add Pickles".

[1]Ambiguity introduces some extra complexities which are beyond scope of this paper.

5. APPRAISAL PROCESSES

We discuss two appraisal variables in a collaboration context, i.e., *relevance* (since other appraisals are only computed for relevant events), and *controllability* (since it is associated with the agent's coping ability). There are other appraisal variables introduced in psychological [15] and computational literature [4]. We have implemented other appraisal variables such as *expectedness* [**?**] and *desirability* [**?**] which do not appear in this paper due to space limitations. The algorithms in this section use mental states of the robot (see Section 3.1) which are formed based on the collaboration structure.

5.1 Relevance

Relevance as an appraisal variable measures the significance of an event for the self. An event can be evaluated to be relevant if it has a non-zero utility [9]. Relevance is an important appraisal variable since the other appraisal variables are meaningful only for relevant events. However, the utility of an event during collaboration is influenced by the other collaborator's actions and mental states, because there is a commitment between collaborators to achieve the shared goal based on the shared plan. Other appraisal models only consider the utility of an event based on the self's (robot's) goal and plan.

Algorithm 1 determines the relevance of the given event with respect to the current mental state. The relevance of the event depends on the significance of the event with respect to the collaboration status, which is determined based on the utility of the event as presented in [4, 9]. Our algorithm for computing the relevance of an event during collaboration involves other factors that other appraisal models do not consider. For instance, the human's perceived emotion, recurrence of a belief, or occurrence of a belief about an unrelated goal by the human play important roles by influencing the utility of an event during collaboration. As a result, evaluating the relevance of events can cause a collaborative robot to respond effectively which can positively impact the status of the shared goal, without dedicating all its resources to every event.

Algorithm 1 (Relevance)

```
function IsEventRelevant(Event ε_t)
    g_t ← recognizeGoal(ε_t)
    U ← getEventUtility(g_t)
    τ_t ← getEmotionalThreshold(g_t)
    if (τ_t ≤ |U|) then return RELEVANT
    else return IRRELEVANT
```

After perceiving an event, the belief about that event represents the event in the robot's mental state. *recognizeGoal* returns the goal to which the current event contributes. We compute the utility ($-1 \leq \mathcal{U} \leq 1$) of the event using the values of the attributes associated with the existing beliefs, and the attributes of the motive associated with the recognized goal (see details below). We use three belief attributes (see Section 3.1) to compute the belief-related part of the utility:

- *Strength*: The extent to which the preconditions (α), postconditions (β), predecessors (λ), and contributing goals (μ) of a goal are known (SATISFIED or UNSATISFIED) makes beliefs about the goal stronger. An UNKNOWN pre/postcondition status of a goal and its predecessors and contributing goals forms weaker beliefs. For instance, if one knows all predecessors of a pursued goal (e.g., "Press Bread Slices") are SATISFIED (i.e., "Spread Peanut Butter" and "Spread Strawberry Jam"), failure of the pursued goal will elicit one's negative emotion (due to the strong beliefs related to the goal); whereas not knowing the status of the goal-related factors (e.g., whether Mary could find the knife to cut the sandwich in half) causes one to form weaker beliefs about the goal.
- *Saliency (S)*: Beliefs related to the focused goal are more salient than beliefs related to any other goal in the plan; according to Figure 4, if one is making a boiled egg sandwich, beliefs related to all of the other *live* (PENDING or IN PROGRESS) goals (e.g. "Pack Sandwich") will be less salient than beliefs related to the focused goal, i.e., "Add Pickles". Beliefs' saliency decreases according to their corresponding *live* goal's distance from the focused goal in the shared plan. *Non-live* goals will not be salient.
- *Persistence (P)*: The recurrence of a belief over time (turns) increases the persistence of the belief. Beliefs occurring only once have the lowest value of persistence. For instance, if Mary keeps saying that she can not find the knife to cut the sandwich in half, one could pursue a new goal outside of the shared plan to acknowledge Mary's concern.

We also use two motive attributes discussed in Section 3.1 to compute the motive related part of the utility ($\mathcal{U}$):

- *Urgency (γ)*: There are two factors impacting the urgency of a motive: a) whether the goal directing the given motive is the predecessor of another goal for which the other collaborator is responsible, and b) whether achieving the goal directing the given motive can mitigate the other collaborator's negative valenced emotion. For instance, if one has a private goal to prepare for making the second sandwich (e.g. get the eggs) while Mary is waiting to get the first sandwich and cut it in half, pressing bread slices and passing them to Mary will be more urgent than one's private goal.
- *Importance (η)*: A motive is important if failure of the directing goal causes an impasse in the shared plan (i.e., no further goal is available to achieve), or achievement of the directing goal removes an existing impasse. For example, if one cannot find white bread on which to spread peanut butter (an impasse to make the peanut butter sandwich), and Mary offers to use wheat bread instead (external motive), the new motive becomes important to remove the impasse in the shared plan.

We provide the utility function ($\mathcal{U}$) in Equation 1. This function uses: saliency (*S*) and persistence (*P*) of the belief related to the recognized goal, the recognized goal's status (υ), and the aggregation of belief and motive attributes (Ψ) according to Equation 2.

$$\mathcal{U}(\varepsilon_t) = \begin{cases} \upsilon P \cdot S^{\Psi} & \Psi > 0 \\ 0 & \Psi = 0 \end{cases} \tag{1}$$

Intuitively, we use υ to generate positive and negative utility values. The υ's value becomes +1 if the status of the corresponding goal is ACHIEVED, PENDING, or IN PROGRESS, and υ's value becomes -1 if the status of the corresponding goal is FAILED, BLOCKED, or INAPPLICABLE. The *P* influences the value of utility only as a coefficient since recurrent beliefs are not formed frequently during collaboration. The Ψ value indicates the magnitude of the influence of beliefs and motives using their attributes. Hence, the Ψ value impacts the saliency value of beliefs exponentially, helping to differentiate between beliefs.

In equation 2, the subscript *k* refers to the *known* goal-related factors (SATISFIED or UNSATISFIED); whereas the subscript *all* includes both *known* and *unknown* goal-related factors. In this equation, both urgency (γ) and importance (η) attributes of motives can impact the outcome of the goal-related belief attributes' ratio, and ultimately the Ψ value.

$$\Psi = \frac{\alpha_k + \beta_k + \lambda_k + \mu_k}{\alpha_{all} + \beta_{all} + \lambda_{all} + \mu_{all}} + \eta + \gamma \tag{2}$$

$$\begin{aligned} \eta, \gamma &\in \mathbb{N}, & \eta, \gamma &\geq 0 \\ \alpha_k, \beta_k, \lambda_k, \mu_k &\in \mathbb{N}, & \alpha_k, \beta_k, \lambda_k, \mu_k &\geq 0 \\ \alpha_{all}, \lambda_{all}, \mu_{all} &\in \mathbb{N}, & \alpha_{all}, \lambda_{all}, \mu_{all} &\geq 0 \\ \beta_{all} &\in \mathbb{N}, & \beta_{all} &\geq 1 \end{aligned}$$

The significance of an event in a collaborative environment is based on the utility of the event and the human's perceived emotion. The human's perceived emotion influences the relevance of the event in the form of a threshold value τ_t. In Equation 3, we use the valence of the perceived emotion ($\mathcal{V}_{e_h}$) to compute τ_t.

$$\tau_t = \begin{cases} 1 - \mathcal{V}_{e_h} & \mathcal{V}_{e_h} > 0 \\ |\mathcal{V}_{e_h}| & \mathcal{V}_{e_h} \leq 0 \end{cases} \tag{3}$$

$$\mathcal{V}_{e_h} \in \mathbb{R}, \qquad -1 \leq \mathcal{V}_{e_h} \leq 1$$

Hence, perceiving human's positive emotion (e.g., happiness) reduces the threshold value which makes the robot find an event RELEVANT with even a slightly positive utility. Similarly, an event can be considered IRRELEVANT even though the utility has a relatively positive value, because of perceiving the human's negative emotion.

5.2 Controllability

Controllability is the extent to which an event can be influenced; it is associated with a robot's ability to cope with an event [4]. Thus, a robot can determine whether an event's outcome can be altered by actions under either of the collaborators' control. In other words, controllability is a measure of a robot's ability to maintain or change a particular state as a consequence of an event.

Algorithm 2 (Controllability)

1: **function** ISEVENTCONTROLLABLE(Event ε_t)
2: $g_t \leftarrow$ *recognizeGoal*(ε_t)
3: $\mathcal{M} \leftarrow$ GETAGENCYRATIO(g_t)
4: $\mathcal{R} \leftarrow$ GETAUTONOMYRATIO(g_t)
5: $\mathcal{P} \leftarrow$ GETSUCCPREDECESSORSRATIO(g_t)
6: $\mathcal{I} \leftarrow$ GETAVAILABLEINPUTS(g_t)
7: $\mathcal{V}_{e_h} \leftarrow$ GETEMOTIONVALENCE(g_t)
8: $\omega \leftarrow$ GETWEIGHTS(g_t)
9: $\mathcal{X} \leftarrow \frac{\omega_0 \cdot \mathcal{M} + \omega_1 \cdot \mathcal{R} + \omega_2 \cdot \mathcal{P} + \omega_3 \cdot \mathcal{I}}{\omega_0 + \omega_1 + \omega_2 + \omega_3} + \mathcal{V}_{e_h}$
10: **if** $(\mathcal{X} > 0)$ **then return** CONTROLLABLE
11: **else return** UNCONTROLLABLE

Controllability is important for the overall architecture. For instance, the robot can choose to ask or negotiate about a collaborative task which is not controllable, or form a new motive to establish an alternative goal for the current uncontrollable event. In general, other mechanisms in the architecture use the controllability output in their decision making processes; meanwhile controllability uses information from the collaboration structure, e.g., predecessors of a goal.

An important determinant of one's emotional response is the sense of control over occurring events. This sense of subjective control is based on one's reasoning about self's power. For instance, the robustness of one's plan for executing actions can increase one's sense of power and subsequently the sense of control. In the collaboration context, we have translated the sense of control into a combination of four different factors including a) *agency* and b) *autonomy* of the robot, as well as the ratios of c) *successful predecessors*, and d) the *available inputs* of a given goal (i.e., g_t) in the shared plan.

In Algorithm 2, we partially compute the controllability of an event based on the above four factors. We use weighted averaging of these factors to determine their impact on the controllability of an event (line 9). The value of all these weights are set to *1.0* for the purpose of simplicity at this stage (**GETWEIGHTS**). We will adjust these weights after further investigating the influence of these factors, and implementing other mechanisms in the overall architecture. We believe that the human's perceived emotion also impacts the controllability of an event (**GETEMOTIONVALENCE**). The $(-1.0 \leq \mathcal{V}_{e_h} \leq 1.0)$ is the valence value of the human's perceived emotion. Positive emotions, e.g., happiness, possess positive values, and negative emotions, e.g., anger, have negative values. The magnitude of this value can change with respect to the intensity of the perceived emotion. Thus, a positive controllability value indicates that an event is CONTROLLABLE; otherwise UNCONTROLLABLE.

GETAGENCYRATIO: *Agency* is the capacity of an individual to act independently in a given environment. In a collaborative environment collaborators are sometimes required to act independently of each other. Hence, they need to have some internal motives that are formed based on their own mental states rather than motives that are reinforced by the other. These internal motives will lead the collaborators to acquire new intentions when required. If the robot's mental state possesses only an internal motive supporting the recognized goal, we consider a maximum agency value denoted as $\mathcal{M}$ in Algorithm 2 (i.e., $\mathcal{M} = 1.0$); otherwise we consider the minimum agency value (i.e., $\mathcal{M} = 0.0$). Note that the process of forming new internal motives is beyond scope of this paper.

GETAUTONOMYRATIO: *Autonomy* is the ability to make decisions without the influence of others, and implies acting on one's own and being responsible for that. In a collaborative environment, tasks are delegated to the collaborators based on their capabilities. Therefore, each collaborator is responsible for the delegated task and the corresponding goal. In Algorithm 2, $\mathcal{R}$ denotes the value of autonomy with regard to the goal g_t. This value $(0.0 \leq \mathcal{R} \leq 1.0)$ is the ratio of the number of goals contributing to g_t for which the robot is responsible over the total number of contributing goals, if the goal associated with the current event is a nonprimitive goal. However, if the associated goal of the current event corresponds to a primitive goal the value of $\mathcal{M}$ would be 0.0 or 1.0. In general, higher autonomy leads to a more positive value of controllability.

GETSUCCPREDECESSORSRATIO: The structure of a shared plan contains the order of the required *predecessors* of a goal. Predecessors of a goal, g_t, are goals that the collaborators should achieve before trying to achieve goal g_t. We use the ratio of successfully achieved predecessors of the recognized goal over the total number of predecessors of the same goal. If all of the predecessors of the given goal are achieved, then $\mathcal{P} = 1.0$ which is the maximum value for $\mathcal{P}$. On the contrary, failure of all of the predecessors will lead to $\mathcal{P} = 0.0$. Therefore, a higher $\mathcal{P}$ value positively impacts the value of controllability for the current event.

GETAVAILABLEINPUTS: Finally, *inputs* of a task are the required elements that the collaborators use to achieve the specified goal of the task. These inputs are also part of the structure of a shared plan. We compute the ratio of the available required inputs over the total required inputs of the goal associated with the current event. This value (denoted as $\mathcal{I}$ in Algorithm 2) will be bound between 0.0 and 1.0. Similar to the other factors in the controllability process, the closer the value of $\mathcal{I}$ gets to 1.0, the more positive impact it has on the overall controllability value of the event.

In summary, the output of these two and other appraisal processes such as *desirability* [**?**] and *expectedness* [**?**] serves as critical input for the other mechanisms and processes (e.g., goal management [**?**]) of the Affective Motivational Collaboration Framework, shown in Figure 3. By providing adequate interpretation of events in the environment, the appraisal mechanism enables the robot to carry out proper collaborative behaviors.

6. EXPERIMENTAL SCENARIO

Our scenario was based on a table top turn-taking game that we designed to simulate installing a solar panel. Participants had to collaborate one-on-one with our robot to complete all the given tasks required to install the solar panel. All the tasks were simple picking up and placing collaborators' available pegs on predefined spots on the board. Each pick-and-place was associated with the robot's or the participant's task. The robot and the participants had their own unique primitive tasks that they had to accomplish in their own turn. The final goal of installing a solar panel required the robot and the participants to accomplish their own individual tasks. Failure of any task could create an impasse during the collaboration.

6.1 The Robot

We conducted our experiment based on a KUKA Youbot (see Figure XYZ). The robot was stationary on top of a desk and was able to pick up and place avaiable pegs corresponding to the robot's task. The robot was operated based on ROS and was receiving commands through the ROS-bridge from either our Affective Motivational Collaboration framework or Disco, see Figure XYZ.

6.2 Interaction Paradigms

The robot interacted via a) speech, b) the corresponding utterance on the screen, c) negative, positive and neutral expression of emotion through an emoticon on the screen. The robot used neutral expression in case of the emotion-ignorance. The interaction was controlled autonomously by the AMC framework in case of the emotion-awareness, and Disco in case of the emotion-ignorance (see Section XYZ). The reasoning about which task should be done and controlling the robot was entirely autonomous. Only the perception of the task failure or achievement by the robot or by the participant was done by a wizard monitoring the collabortion outside of the test area. The interaction was structured based on the exact same goals in an HTN for both conditions. The robot was using the same utterances in both conditions. In emotion-aware condition only if the participant was expressing a negative emotion in case of a failure the robot was using a different utterance in compare to the participant's positive or neutral expression of emotion; i.e., the robot's utterances were identical in emotion-aware and emotion-ignorance cases if in the latter the participant reported (expressed) a positive or a neutral emotion. At the beginning of each collaboration the robot asked each participant to achieve the overall shared goal, i.e., "installing the solar panel". Then, before achieving a new goal, the robot informed the participant about the higher level nonprimitive goal of which the primitives were going to be achieved. The same procedure was used by the robot if there was a decision for switching to another nonprimitive due to the failure of the task achieving the current goal. For example, ... (see Figure XYZ – for branches!!!). After achieving a new primitive goal, the robot either informed the human keeping the ground for the next goal to achieve, or informed and passed the ground to the human to execute the next task with repoect to the human's goal. In case of the human's turn, the robot waited for the human to do a task, then the wizard let the robot know whether the human's goal was achieved or not. Afterwards the robot was making a decision about which goal to pursue and was informing human accordingly. The same entire procedure was applied to both conditions.

6.3 Environment and Tasks

7. EXPERIMENTAL DESIGN

8. EXPERIMENTAL SCENARIO

9. STUDY DESIGN AND PROCEDURE

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9.2 Robotic Implementation

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10.2 Setting and Conditions

10.3 Procedure

10.4 Measurements

10.5 Evaluation Results

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11.2 Emotion A Robot

11.3 Generalization and Limitations

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14. ACKNOWLEDGMENTS

15. ADDITIONAL AUTHORS

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