Affective Motivational Collaboration Theory

by

Mahni Shayganfar - mshayganfar@wpi.edu

A PhD Dissertation

Presented at

WORCESTER POLYTECHNIC INSTITUTE

in partial fulfillment of the requirements for the

DOCTOR OF PHILOSOPHY

in

Computer Science

November 2016

APPROVED

Professor Charles Rich, Thesis Advisor

Professor Candace L. Sidner, Thesis Co-Advisor

Professor John E. Laird, Thesis Committee Member

Professor Stacy Marsella, Thesis Committee Member

ABSTRACT

Abstract Here!

ACKNOWLEDGMENTS

Acknowledgments Here!

Contents

List of Figures

List of Tables

CHAPTER 1
INTRODUCTION

1.1 Motivation

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.

A key aspect of the sociability of robots is their ability to collaborate with humans in the same environment. Collaboration is a coordinated activity in which the participants work jointly to satisfy a shared goal [10]. There are many challenges in achieving a successful collaboration between robots and humans. To meet these challenges, it is crucial to understand what makes a collaboration not only successful, but also efficient. Existing computational models of collaboration explain some of the important concepts underlying collaboration; such as the presence of a reason for collaborators' commitment, and the necessity of communicating about mental states in order to maintain progress over the course of a collaboration. The most prominent collaboration theories are based on plans and intentions [4] [10] [14], and are derived from Bratman's BDI architecture [1]. Two theories, Joint Intentions

[4] and SharedPlans [8, 9, 10], have been used to support teamwork and collaboration between humans and robots or virtual agents [2] [18] [21] [24]. However, these theories explain only the structure of a collaboration. For instance, in SharedPlans theory collaborators build a shared plan containing a collection of beliefs and intentions about the actions in the plan. Collaborators communicate these beliefs and intentions via utterances about actions that contribute to the shared plan. This communication leads to the incremental construction of a shared plan, and ultimately successful completion of the collaboration. In contrast, in Joint Intentions theory, the notion of joint intention is viewed as a persistent commitment of the team members to a shared goal. In this theory, once an agent enters into a joint commitment with other agents, it should communicate its private beliefs to other team members.

Although existing collaboration theories explain the important elements of a collaboration structure, the underlying processes required to dynamically create, use, and maintain the elements of this structure are largely unexplained. For instance, a general mechanism has yet to be developed that allows an agent to effectively integrate the influence of its collaborator's perceived or anticipated emotions into its own cognitive mechanisms to prevent shared task failures while maintaining collaborative behavior. Therefore, a process view of collaboration must include certain key elements. It should inherently involve social interactions since all collaborations occur between social agents, and it should essentially constitute a means of modifying the content of social interaction as the collaboration unfolds. The underlying processes of emotions possess these two properties, and social functions of emotions explain some aspects of the underlying processes in collaboration. This thesis makes the case for emotion-driven processes within collaboration and demonstrates how it furthers collaboration between humans and robots.

1.2 Thesis Statement and Scope

In this thesis, we develop and validate a framework based on *Affective Motivational Collaboration Theory* which can improve the effectiveness of collaboration between agents/robots and humans. This thesis is established based on the reciprocal influence of collaboration structure and the appraisal processes in a dyadic collaboration. We focus only on two-participant collaboration; teamwork collaboration is out of our scope. Furthermore, this work focuses on a) the influence of emotion-regulated processes on the collaboration structure, and b) prediction of the observable behaviors of the other during a collaborative interaction.

We describe the cognitive processes involved in a collaboration in the context of a cognitive architecture. There are several well-developed cognitive architectures, e.g., Soar [12] and ACT-R [11], each with different approaches to defining the basic cognitive and perceptual operations. There have also been efforts to integrate affect into these architectures [5, 16]. In general, however, these cognitive architectures do not focus on processes to specifically produce emotion-regulated goal-driven collaborative behaviors. At the same time, existing collaboration theories, e.g., SharedPlans [10] theory, focus on describing the structure of a collaboration in terms of fundamental mental states, e.g., mutual beliefs or joint intentions. However, they do not describe the associated processes, their relationships, and influences on each other. *Affective Motivational Collaboration Theory* deals with some of the major affect-driven processes having an impact on the collaboration structure. This theory is informed by research in psychology and artificial intelligence which is reviewed in Chapter 2. Our contribution, generally speaking, is to synthesize prior work on appraisal and collaboration, and motivation to provide a new theory which describes some of the prominent emotion-regulated goal-driven phenomena in a dyadic collaboration.

1.3 Contributions

Throughout this work we aim to show how a robot can leverage emotion-driven processes using appraisal algorithms to improve collaboration with humans. As such, in this thesis work, we introduce a novel framework, called Affective Motivational Collaboration (AMC) framework, which allows a robotic agent to collaborate with a human while incoporating the underlying emotion-driven processes and the expressed emotion of the human collaborator. Such a framework is built based on computational models of collaboration and appraisal allowing for task-driven interaction with robots or other agents. The theoretical foundation, computational models and algorithms as well as the overall framework, and the end-to-end evaluation of the framework make the following contributions:

1. **Introducing *Affective Motivational Collaboration Theory*:**

   (Chapter 3) As mentioned earlier, since the theoretical foundation of AMC framework is built on the combination of SharedPlans theory of collaboration [10] and cognitive appraisal theory of emotions [17] [20], one of the contributions of our work is to introduce theoretical concepts incorporating key notions of both theories in a dyadic collaboration context. Applying cognitive appraisal theory in the collaboration context is novel. Other models of the appraisal theory have not paid attention to the dynamics of the collaboration.

2. **Developing new computational models and algorithms for *Affective Motivational Collaboration Framework*:**

   (Chapter 4) Another contribution of our work is to create computational models and algorithms to compute the value of appraisal variables in a dyadic collaboration. We use the collaboration structure to compute appraisal variables. Reciprocally, we use the evaluative nature of the appraisal to make changes to the collaboration structure as required. We have also developed

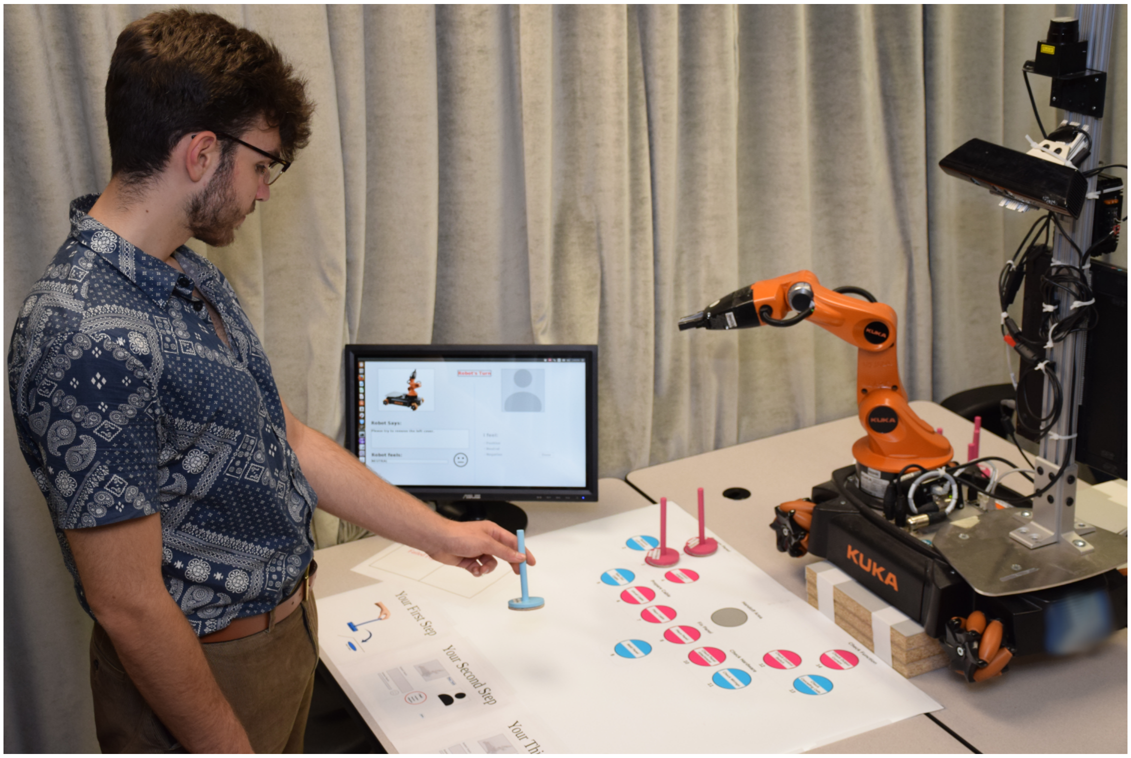

Figure 1.1: A robotic arm collaborating with a human to achieve a shared goal using *Affective Motivational Collaboration Framework*.

a new algorithm for emotion-driven goal management in the context of collaboration. Goal management is one of the important functions of emotions during collaboration. Existing models and implementations of emotions focus only on how emotions regulate and control internal processes and sometimes behaviors. This part of our work shows how appraisal components of the self and the human collaborator contributes to goal management as an emotion function.

3. **Developing a computational framework based on *Affective Motivational Collaboration Theory*:**

   (Chapter 5) In order to evaluate our computational models and algorithms within an interaction with human collaborators, we have developed a computational framework based on our theoretical foundations in *Affective Motiva-*

tional Collaboration Theory. Our computational framework implements the key concepts related to *Affective Motivational Collaboration Theory* as well as minimal implementation of other processes which are required for validation of the model but are not part of this thesis' contributions. The emphasis of the model is on the underlying cognitive processes of collaboration and appraisal concepts, rather than the Perception and the Action mechanisms.

4. **Validating *Affective Motivational Collaboration Theory:***

   (Chapters 4 and 6) We have conducted two user studies a) to validate our appraisal algorithms before further development of our framework, and b) to investigate the overall functionality of our framework within an end-to-end system evaluation with participants and a robot. The second user study was also conducted to evaluate the benefit of using our computational framework in human-robot collaboration. In the first user study, we crowd sourced our questionnaires to test our hypothesis that humans and our algorithms will provide similar answers to questions related to different factors within our appraisal algorithms. In the second user study, we investigated the importance of emotional awareness in human-robot collaboration, and the overall functionality of the AMC framework with the participants in our study environment.

CHAPTER 2

BACKGROUND AND RELATED WORK

2.1 Computational Collaboration Theories

2.1.1 Shared-Plans Theory

2.1.2 Joint-Intentions Theory

2.1.3 Hybrid Theories

2.1.4 Similarities and Differences

2.1.5 Applications of Collaboration Theories

2.2 Affective Computing

2.2.1 Affect and Emotions

2.2.2 Functions of Emotions

2.2.3 Motivation and Theory of Mind

2.3 Computational Models of Emotions

2.3.1 Appraisal Theory

2.3.2 Other Computational Models

2.3.3 Similarities and Differences

2.3.4 Applications in Autonomous Agents and Robots

CHAPTER 3
AFFECTIVE MOTIVATIONAL COLLABORATION THEORY

3.1 Introduction

3.1.1 Scenario

3.1.2 Example of a Collaborative Interaction

3.2 Design and Architecture

3.2.1 Mechanisms

3.2.2 Functions of Emotions

3.2.3 Mental States

3.2.4 Attributes of Mental States

CHAPTER 4
APPRAISAL PROCESSES IN COLLABORATION CONTEXT

4.1 Introduction

In this chapter, we focus on the specific problem of appraising the *Relevance* (since other appraisals are only computed for relevant events), *Desirability* (since it discriminates facilitating and inhibitory events towards the collaboration progress), *Expectedness* (since it underlies a collaborative robot's attention), and *Controllability* (since it is associated with the agent's coping ability) of events within a collaborative interaction. Our contribution is to ground general appraisal concepts in the specific context and structure of collaboration.

There are several appraisal models (e.g., EMA [17]) 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 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.

4.2 Appraisal and Collaboration

In this section, we focus on a small part of a larger framework based on our Affective Motivational Collaboration Theory. We describe the methods which retrieve information about the collaboration structure, and are used to compute the values of appraisal variables. Then, we introduce our algorithms implemented to compute the value of four appraisal variables depicted in Figure 4.1.

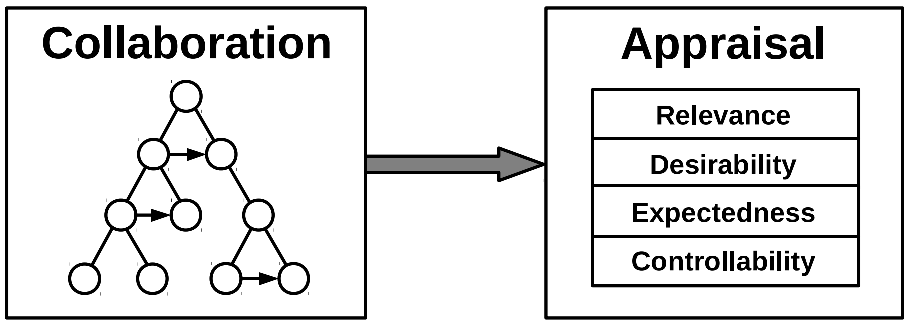

Figure 4.1: Using Collaboration structure in Appraisal (mechanisms in our framework).

4.3 Collaboration

The Collaboration mechanism constructs a hierarchy of goals associated with tasks in the form of a hierarchical task network (see Figure 4.2), and also manages and 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 keeps track of 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 briefly describe the methods which retrieve information about the collaboration structure, and are used in our algorithms 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.

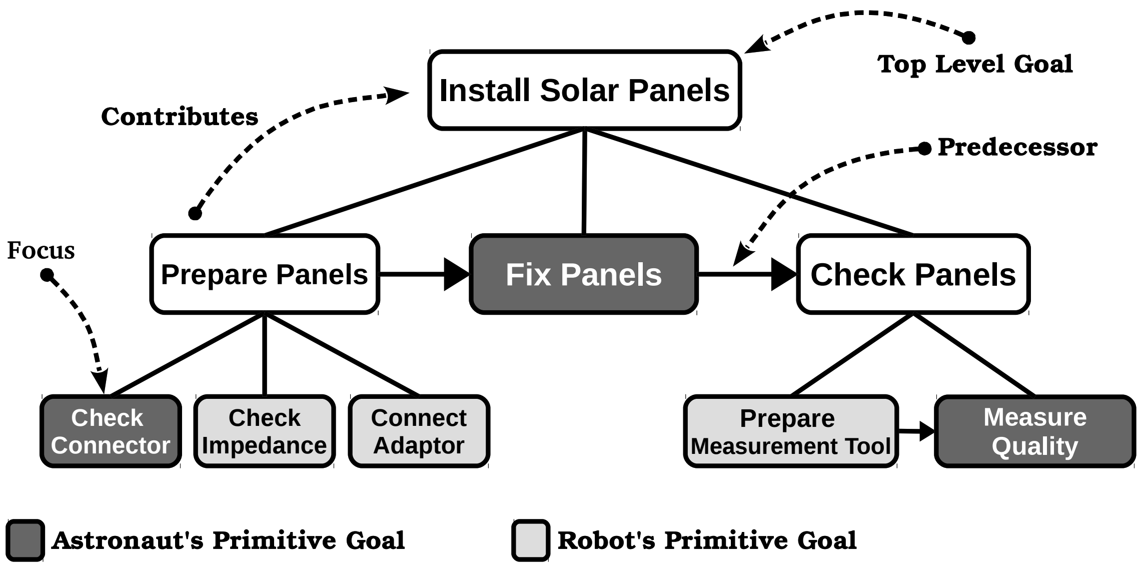

Figure 4.2: Collaboration structure (shared plan).

- *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, "Check Connector" is the current (focused) goal and it is PENDING, and the "Prepare Panels" and "Install Solar Panels" are IN PROGRESS. The focused goal is the goal that the robot currently pursues.

- *getTopLevelGoal*(g_t) returns g_t's top level goal.

- *precondStatus*(g_t) returns the status of the precondition for the given goal whether it is SATISFIED, UNSATISFIED or UNKNOWN. For instance, the precondition for fixing a panel is whether the panel is appropriately located on

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

its frame.

- *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*.

- *isFocusShift(g_t)* returns *true* if the given goal is not the previous focus (top of the stack); otherwise returns *false*.

- *isNecessaryFocusShift(g_t)* returns *true* if the status of the previous focus was ACHIEVED; otherwise returns *false* [13].

- *isPath(g_1, g_2)* returns *true* if there is a path between g_1 and g_2 in a plan tree structure; 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 "Fix Panels" requires inputs such as *welding tool* and *panel*.

- *isAvailable(g_t)* returns whether the given input is available. For instance, whether the *welding tool* is available for the goal "Fix Panels".

- *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 (jointly) can be partly responsible for a nonprimitive goal, while each (self or other) is responsible for one or more primitive goals. For instance, both the Robot and the Astronaut are responsible for the nonprimitive goal of "Install Solar Panels", whereas it is only the Robot who is responsible for the primitive goal of "Prepare Measurement Tool".

4.4 Appraisal Processes

As we mentioned earlier, We consider four appraisal variables to be the most important appraisal variables in a collaboration context, i.e., Relevance, Desirability, Expectedness, and Controllability. There are other appraisal variables introduced in psychological [20] and computational literature [7]. We believe most of these variables can be straightforwardly added to our appraisal mechanism whenever they are required. All of the algorithms in this section use mental states of the robot (discussed in Section 3.2.3) which are formed based on the collaboration structure. These algorithms use the corresponding recognized goal of the most recent event at each turn.

4.4.1 Relevance

Relevance is an important appraisal variable since the other appraisal variables are meaningful only for relevant events. 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 [17]. However, the utility of an event is also influenced by the other collaborator's emotional expressions as the reflection of the other collaborator's mental state with respect to the status of the collaborative environment. Other appraisal models only consider the utility of an event based on the self'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 [7, 17]. 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.

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, unless it is *ambiguous*; g_t represents the shared goal at time (turn) t within the shared plan. 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 3.2.3) to compute the belief-related part of the utility:

Algorithm 1 (Relevance)

function ISEVENTRELEVANT(Event ε_t)

  $g_t \leftarrow \textit{recognizeGoal}(\varepsilon_t)$

  $\mathcal{U} \leftarrow$ GETEVENTUTILITY(g_t)
  $\tau_t \leftarrow$ GETEMOTIONALTHRESHOLD(g_t)

  if ($\tau_t \leq |\mathcal{U}|$) **then**
    return RELEVANT
  else
    return IRRELEVANT

- *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 and 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., "Check Panels") are SATISFIED (i.e., "Fix Panels" and "Prepare Panels"), 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 the Astronaut could find the tool to fix a panel) 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 4.2, if one of the collaborators is preparing a solar panel, beliefs related to all of the other *live* (PENDING or IN PROGRESS) goals (e.g. "Connect Adaptor") will be less salient than beliefs related to the focused goal, i.e., "Check Connector". 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 the Astronaut keeps saying that she can not find the measurement tool to check the connector, Robot could pursue a new goal outside of the shared plan to acknowledge Astronaut's concern.

We also use two motive attributes discussed in Section 3.2.3 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 the Robot has a private goal to fetch another panel while the Astronaut is waiting for the Robot to connect the adaptor, connecting the adaptor will be more urgent than Robot'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 the Robot cannot find the adaptor (an impasse to connect the adaptor), and the Astronaut provides another adaptor (external motive), the new motive becomes important to remove the impasse in the shared plan.

We provide the utility function ($\mathcal{U}$) in Equation 4.1. 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 4.2.

$$\mathcal{U}(\varepsilon_t) = \begin{cases} \upsilon P \cdot S^{\Psi} & \Psi > 0 \\ 0 & \Psi = 0 \end{cases} \tag{4.1}$$

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 4.2, 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.

$$\Psi = \frac{\alpha_k + \beta_k + \lambda_k + \mu_k}{\alpha_{all} + \beta_{all} + \lambda_{all} + \mu_{all}} + \eta + \gamma \tag{4.2}$$

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

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 4.3, we use the valence of the perceived emotion ($\mathcal{V}_{e_h}$) to compute τ_t.

$$\tau_t = \begin{cases} 1 - \mathcal{V}_{e_h} & \mathcal{V}_{e_h} > 0 \\ |\mathcal{V}_{e_h}| & \mathcal{V}_{e_h} \leq 0 \end{cases} \tag{4.3}$$

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

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.

4.4.2 Desirability

Desirability characterizes the value of an event to the robot in terms of whether the event facilitates or thwarts the collaboration goal. Desirability captures the valence of an event with respect to the robot's preferences [7]. In a collaborative robot, preferences are biased towards those events facilitating progress in the collaboration. Desirability plays an important role in the overall architecture; it makes the processes involved in the other mechanisms (e.g., Motivation and Theory of Mind) and consequently the robot's mental state, congruent with the collaboration status which is a collaborative robot's desire. Therefore, it causes the robot to dismiss events causing inconsistencies in the robot's collaborative behavior. Moreover, desirability is also crucial from the collaboration's point of view.

Algorithm 2 provides a process in which the desirability of an event is computed with regard to the status of the shared goal; i.e., it operates based on whether and how the event changes the status of the current shared goal. It distinguishes between the top level goal and the current goal because the top level goal's change of status

Algorithm 2 (Desirability)

```
function IsEventDesirable(Event ε_t)

    g_t ← recognizeGoal(ε_t)
    g_top ← getTopLevelGoal(g_t)

    if (getGoalStatus(g_top) = ACHIEVED) then
        return MOST-DESIRABLE
    else if (getGoalStatus(g_top) = FAILED) then
        return MOST-UNDESIRABLE
    else if (getGoalStatus(g_top) = BLOCKED)
   (getGoalStatus(g_top) = INAPPLICABLE) then
        return UNDESIRABLE
    else if (getGoalStatus(g_top) = PENDING)
   (getGoalStatus(g_top) = INPROGRESS) then

        if (getGoalStatus(g_t) = ACHIEVED) then
            return DESIRABLE
        else if (getGoalStatus(g_t) = FAILED) then
            return MOST-UNDESIRABLE
        else if (getGoalStatus(g_t) = BLOCKED)
       (getGoalStatus(g_t) = INAPPLICABLE) then
            return UNDESIRABLE
        else if (getGoalStatus(g_t) = PENDING)
       (getGoalStatus(g_t) = INPROGRESS) then
            return NEUTRAL
```

attains a higher positive or negative value of desirability. For instance, failure of the top level goal (e.g., installing solar panel) is more undesirable than failure of a primitive goal (e.g., measuring the quality of the installed panel).

A top level goal' status must be ACHIEVED (i.e., SATISFIED postcondition) to consider the event MOST-DESIRABLE. When the goal's status is FAILED (i.e., UNSATISFIED postcondition) or BLOCKED, the associated event has the MOST-UNDESIRABLE or UNDESIRABLE values respectively. A goal is BLOCKED if any of the required goals or goals recursively through the parent goal are not ACHIEVED. An INAPPLICABLE goal is also considered as UNDESIRABLE. A goal is INAPPLICABLE if any of its predecessors are not ACHIEVED, and/or its preconditions are not SATISFIED. For

PENDING and INPROGRESS top level goals, the status of the current goal associated with the top level goal determines the status of the event ε_t. Only a non-primitive goal can have INPROGRESS status, if it has been started but is not yet completed. A goal can be PENDING if it is live, or if it is a non-primitive goal that has not been started yet. ACHIEVED current goals mark an event (ε_t) as DESIRABLE, while FAILED or BLOCKED current goals render the event associated with them as MOST-UNDESIRABLE and UNDESIRABLE respectively. PENDING or INPROGRESS current goals mark their associated events as NEUTRAL.

4.4.3 Expectedness

Expectedness is the extent to which the truth value of a state could have been predicted from causal interpretation of an event. In the collaboration context the expectedness of an event evaluates the congruency of the event with respect to the existing knowledge about the shared goal. Thus, expectedness underlies a collaborative robot's attention. The collaboration mechanism uses expectedness to maintain the robot's attention and subsequently its mental state with respect to the shared goal. Reciprocally, the appraisal mechanism uses the underlying information of the collaboration structure to evaluate the expectedness of an event [22].

In Algorithm 3 we provide the process of computing the expectedness based on the shared plan and status of the shared goal. The key point in this algorithm is the status of the current shared goal (g_t), which is associated with the event ε_t and its relationship with the top level goal (g_{top}).

The intuition captured here is that one expects the current goal to be finished before undertaking another activity, but the goals that can be the next focus of attention are also to be expected. Therefore, if the goal is live, the algorithm checks whether the goal has not changed, or whether the interpretation of the last event results in a necessary focus shift. Shifting the focus to a new goal is necessary when the former goal is achieved and a new goal is required. Consequently the new event is the MOST-EXPECTED one. However, even if the focus shift is not necessary, the

Algorithm 3 (Expectedness)

function IsEventExpected(Event ε_t)

  $g_t \leftarrow \mathit{recognizeGoal}(\varepsilon_t)$
  $g_{top} \leftarrow \mathit{getTopLevelGoal}(g_t)$

  if $(\mathit{isLive}(g_t))$ **then**
    if $(\neg \mathit{isFocusShift}(g_t)$
    $\mathit{isNeccessaryFocusShift}(g_t))$ **then**
      return MOST-EXPECTED
    else
      return EXPECTED
  else
    if $(\mathit{isPath}(g_t, g_{top}))$ **then**
      return UNEXPECTED
    else
      return MOST-UNEXPECTED

new event can be considered as EXPECTED, since the corresponding goal is already live. For goals that have not yet been started (that is, are not live), the algorithm must determine how unexpected it would be to pursue one now; if the goal is at least in the plan, i.e., on the path to the top level goal, it is just UNEXPECTED while any others are MOST-UNEXPECTED.

4.4.4 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 [7]. 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.

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

Algorithm 4 (Controllability)

1: **function** IsEventControllable(Event ε_t)
2: $\quad g_t \leftarrow \textit{recognizeGoal}(\varepsilon_t)$

3: $\quad \mathcal{M} \leftarrow$ GetAgencyRatio(g_t)
4: $\quad \mathcal{R} \leftarrow$ GetAutonomyRatio(g_t)

5: $\quad \mathcal{P} \leftarrow$ GetSuccPredecessorsRatio(g_t)
6: $\quad \mathcal{I} \leftarrow$ GetAvailableInputs(g_t)

7: $\quad \mathcal{V}_{e_h} \leftarrow$ getEmotionValence(g_t)
8: $\quad \omega \leftarrow$ getWeights(g_t)

9: $\quad \mathcal{X} \leftarrow \frac{\omega_0 \cdot \mathcal{M} + \omega_1 \cdot \mathcal{R} + \omega_2 \cdot \mathcal{P} + \omega_3 \cdot \mathcal{I}}{\omega_0 + \omega_1 + \omega_2 + \omega_3} + \mathcal{V}_{e_h}$

10: $\quad$ **if** $(\mathcal{X} > 0)$ **then**
11: $\quad\quad$ **return** CONTROLLABLE
12: $\quad$ **else**
13: $\quad\quad$ **return** UNCONTROLLABLE

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 4, 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 4 (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 4, $\mathcal{R}$ 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 4) 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 four appraisal processes serves as critical input for the other mechanisms of the Affective Motivational Collaboration Framework, shown in Chapter 3. By providing adequate interpretation of events in the collaborative environment, the appraisal mechanism enables the robot to carry out proper collaborative behaviors.

4.5 Experimental Scenario

To minimize the background knowledge necessary for our test subjects, we used a simple domestic example of preparing a peanut butter and jelly sandwich, and a hard boiled egg sandwich for a hiking trip.

4.5.1 Tasks

Participants were asked to carry out a sequence of hypothetical collaborative tasks between them and an imaginary friend, Mary, in order to accomplish their goal of preparing two sandwiches. All the tasks were simple and did not require the participants to solve a particular problem rather accomplish something as they do in their day to day life.

4.6 Evaluation

4.6.1 Hypothesis

We conducted this user study to test our hypothesis that humans and our algorithms will provide similar answers to questions related to different factors used to compute four appraisal variables: relevance, desirability, expectedness, and controllability.

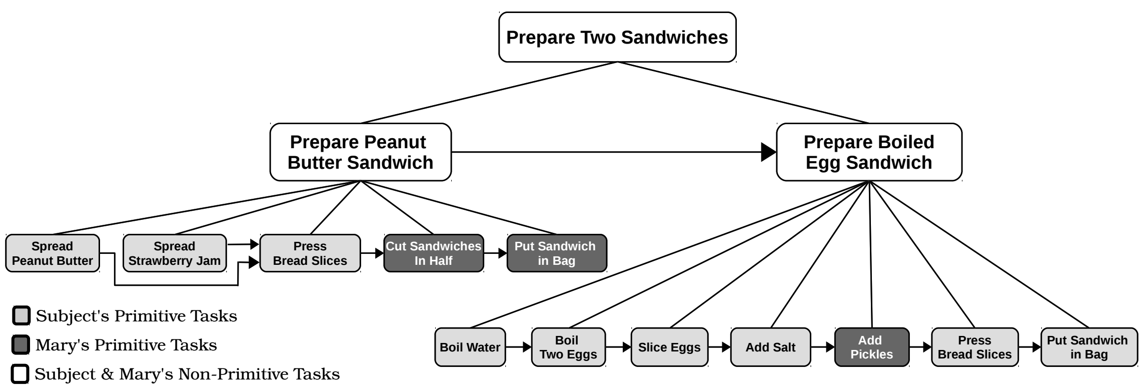

Figure 4.3: Collaboration Task Model for the Evaluation.

4.6.2 Procedure

We conducted a between-subject user study using an online crowdsourcing website – CrowdFlower[1]. We had a questionnaire for each appraisal variable. There were 12 questions (including 2 test questions) in the controllability and expectedness ques-

[1] http://www.crowdflower.com

tionnaires, 14 questions (including 2 test questions) in the desirability questionnaire, and 22 questions (including 3 test questions) in the relevance questionnaire.

We provided textual and graphical instructions for both questionnaires; Figure 4.3 shows the corresponding task model. The instructions presented a sequence of hypothetical collaborative tasks to be carried out by the test subject and an imaginary friend in order to accomplish their goal of preparing two sandwiches. We also provided a simple definition and an example of each appraisal variable. The collaboration structure and the instructions were the same for both questionnaires. The questions introduced specific situations related to the shared plan, which included blocked tasks and failure or achievement of a shared goal. Each question provided three answers which were counterbalanced in the questionnaire. We provided an option like C in all questions (see Figure 4.4), because we did not want to force participants to choose between two options when they did not have a good reason. There were two questions designed based on each factor that we use in our algorithms (see Section 4.4). The questions were randomly placed in the questionnaire. Figure 4.4 shows an example question from the relevance questionnaire which was designed to test whether participants perceive saliency as a factor in relevance. The input for our algorithms was the task model depicted in Figure 4.3.

4.6.3 Measurement

Each question was designed based on different factors that we use in our algorithms (see Section 4.4). Here, we present four example questions from the expectedness, controllability, desirability, and relevance questionnaires, and describe how each question relates to a specific factor within the corresponding algorithm. The input for our algorithms was the task model depicted in Figure 4.3.

Figure 4.4 shows the example question from the expectedness questionnaire. In this example, with respect to Algorithm 3 (line 6), option A is more expected because the task related to this option provides the next available task in the focus stack (see the task model in Figure 4.3). Although the task in option B is part of

Imagine you have pressed the two slices of bread (one covered with strawberry jam and one covered with peanut butter) together and passed it to Mary. Which of the following two actions is **more expected**?

A. Mary puts the given sandwich into a zip lock bag after cutting it in half.

B. Mary puts some pickles on another slice of bread.

C. Equally expected.

Figure 4.4: Example Expectedness Question.

the existing task model, it is considered as unexpected by our algorithm, since it is not live in the plan. We provided option C to determine whether the participants will similarly differentiate between these two options. This question was presented to the participants to determine whether their decision for the expectedness of this event is similar to the output of the expectedness algorithm. For this question, the human decision was 97% similar to the algorithm's output. Average results for the expectedness questionnaire are presented in Table 4.1.

Imagine you want to make a peanut butter sandwich. Which of the following two actions is **more controllable**?

A. You can spread the peanut butter on one slice of bread and you need Mary to spread strawberry jam on the second slice of bread.

B. You can spread the peanut butter on one slice of bread and strawberry jam on the second slice of bread.

C. Equally controllable.

Figure 4.5: Example Controllability Question.

Figure 4.5 shows an example question from the controllability questionnaire. The algorithm's output is option B, and is determined by Algorithm 4 (line 3), similarly to the expectedness example above. In this example, option B is more controllable than option A, because the self over total ratio of the responsibility of the predecessors of the given task (see *Autonomy* in Section 4.4.4) is higher than the ratio in option A; i.e., self is responsible to spread peanut butter on one slice of bread and strawberry jam on another slice of bread. In this question, the humans decision was 90% in agreement with the algorithm's output.

Figure 4.6 shows an example question from the desirability questionnaire. The output based on the Algorithm 2 (line 14) is option C, since in both option A and option B, the focus goal has been achieved successfully. Therefore, in this example, both options A and B are desirable. The humans' decision was 77% in agreement with the algorithm's output in this question.

Which of the following two actions is **more desirable**?

A. Imagine you pressed two slices of bread together with peanut butter and strawberry jam on them, and passed them to Mary. Mary cuts the peanut butter sandwich in half and puts them in the zip lock bag.

B. Imagine you want to make the egg sandwich. You have sliced the eggs, put them on one slice of bread, salted them, and waiting for Mary to put some pickles on your eggs. Mary puts some pickles on your eggs.

C. Equally desirable.

Figure 4.6: Example Desirability Question.

In the example shown in Figure 4.7, with respect to Algorithm 1, option A is relevant because of Mary's perceived negative emotion (see Equation 4.1). Although option B is relevant (since it achieves the next goal in the shared plan), 83% of participants consider it as less relevant than option A; we believe this is due to the effect of Mary's perceived negative emotion which also generates a higher utility value in our relevance algorithm. Another question also tested belief saliency. However, the options provided only related to the shared plan (i.e., no human emotions in the options). In this case 87% of participants chose the option that accomplished the next goal in the shared plan. Interestingly, when confronted with a negative emotion from their collaborator, human participants deviated from the shared plan and found their collaborator's emotion more relevant than the original plan. It is noteworthy that in both the absence and the presence of emotions the participants chose the more salient option with respect to our definition of saliency, which was not referenced or provided in the questionnaire.

Furthermore, as we mentioned earlier, there were two questions related to each factor in our algorithms. Because each question was asking about a specific fac-

Imagine you have made the peanut butter sandwich and passed it to Mary to cut it in half. Which of the following two actions is **more relevant**?

A. Mary starts crying since she cut her finger with a knife.

B. You begin to boil the water to boil the eggs for your second sandwich.

C. Equally relevant.

Figure 4.7: Example Relevance Question.

tor, we were able to perform a sensitivity analysis, similar to the saliency example presented above. We observed similar results for other factors for all four variables.

4.6.4 Participants

Each participant group originally had 40 participants. We limited the participant pools to those with the highest confidence level on the crowdsourcing website in the United States, Britain, and Australia. Test questions were included to check the sanity of the answers. We eliminated participants providing wrong answers to our sanity questions, and participants with answering times less than 2 minutes. The final number of accepted participants in each group is provided in Table 4.1.

Table 4.1: Evaluation Results

appraisal variables	# of participants	mean	stdev	p-value
Relevance	29	0.713	0.107	<0.001
Desirability	35	0.778	0.150	<0.001
Expectedness	33	0.785	0.120	<0.001
Controllability	33	0.743	0.158	<0.001

4.7 Results

Average results and standard deviation of the fractions of participants' answers agreeing with our algorithms output for both questionnaires are presented in Table 4.1. Each question had 3 answers. Therefore, a random distribution would result in 33% agreement with our algorithms' output. However, the average ratio indicating similarity between participants decisions and the output of our algorithms is significantly higher than 33%. The total number of participants' answers similar to the *relevance* algorithm (n=29) averaged 71.3% (s=10.7%), the *desirability* algorithm (n=35) averaged 77.8% (s=15.0%), the *expectedness* algorithm (n=33) averaged 78.5% (s=12.0%), and the *controllability* algorithm (n=33) averaged 74.3% (s=15.8%). It is worth noting that the human participants agreed 100% on some questions, while on some other questions there was a much lower level of agreement. Our results indicate that people largely performed as our hypothesis predicted. The p-values obtained based on a one-tailed z-test (see Table 4.1) show the probability of human participants' answers being generated from a random set. The very small p-values indicate that the data set is not random; in fact, the high percentage of similarity confirms our hypothesis and shows that the algorithms can help us to model appraisal in a collaboration.

4.7.1 Controllability

4.7.2 Desirability

4.7.3 Expectedness

4.7.4 Relevance

4.8 Discussion

4.9 Conclusions

CHAPTER 5
COMPUTATIONAL FRAMEWORK

5.1 Introduction

Current computational theories used for human-robot collaboration specify the structure of collaborative activities, but are weak on the underlying processes that generate and maintain these structures. We argue that emotions are crucial to these underlying processes and we have developed a new computational theory, called Affective Motivational Collaboration Theory, that combines emotion-based processes, such as appraisal and coping, with collaboration processes, such as planning, in a single unified framework. 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. We have investigated the mutual influences of affective and collaborative processes in a cognitive theory to support interaction between humans and robots or virtual agents. We build primarily on the *cognitive appraisal* theory of emotions and the *SharedPlans* theory of collaboration to investigate the structure, fundamental processes and functions of emotions in a collaboration. We have developed new algorithms for appraisal processes as part of a new overall computational model. We have evaluated our implemented appraisal algorithms by conducting an online user study.

Although existing collaboration theories explain the important elements of a collaboration structure, the underlying processes required to dynamically create, use, and maintain the elements of this structure are largely unexplained. For instance, a general mechanism has yet to be developed that allows an agent to effectively integrate the influence of its collaborator's perceived or anticipated emotions into its own cognitive mechanisms to prevent shared task failures while maintaining collaborative behavior. Therefore, a process view of collaboration must include certain key elements. It should inherently involve social interactions since all collaborations occur between social agents, and it should essentially constitute a means of modifying the content of social interaction as the collaboration unfolds. The underlying processes of emotions possess these two properties, and social functions of emotions explain some aspects of the underlying processes in collaboration. 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.

There is also a communicative aspect of emotions. For instance, emotions are often intended to convey information to others [6]. Emotions are also involved in verbal behaviors. For instance, an utterance can include both content and relational meaning. An emotion might appear to be elicited by the content of the utterance, but in fact be an individual's response to the relational meaning [19]. The interpretation of these relational meanings are handled by the appraisal of events. Appraisal processes give us a way to view emotion as social [23]. Meaning is created by an individual's social experiences in the social world, and individuals communicate these meanings through utterances. Consequently, the meaning of these utterances and the emotional communication change the dynamic of social interactions. A successful and effective emotional communication necessitates ongoing reciprocal adjustments between interactants that can happen based on interpretation of each other's behaviors [15]. This adjustment procedure requires a baseline and an assessment procedure. While the components of the collaboration structure, e.g., shared plan, provide the baseline, emotion-related processes (e.g., appraisal) provide the assessment procedure.

5.2 System Overview

5.3 Components of the Architecture

5.3.1 Mental States

5.3.2 Collaboration

5.3.3 Appraisal

5.3.4 Coping

5.3.5 Motivation

5.3.6 Theory of Mind

5.3.7 Perception

5.3.8 Action

CHAPTER 6
IMPROVING HUMAN-ROBOT COLLABORATION USING EMOTIONAL-AWARENESS

6.1 Introduction

As mentioned earlier, collaborative robots need to take into account humans' internal states while making decisions during collaboration. Humans express emotions to reveal their internal states in social contexts including collaboration [3]. Due to the existence of such expressions robots' emotional-awareness can improve the quality of collaboration in terms of humans' perception of performance and preferences. Hence, collaborative robots need to include affect-driven mechanisms in their decision-making processes to be able to interpret and generate appropriate responses and behaviors. Our aim in this setup was to study the importance of emotional awareness and the underlying affect-driven processes in human-robot collaboration. We examined how emotional-awareness impacts different aspects of humans' preferences by comparing the results from our participants collaborating with an emotion-aware and an emotion-ignorant robot.

6.2 Implementation

The implementation of this user-study included three separate parts. The first part incorporated the Affective Motivational Collaboration Framework consisting of all Mental Processes (see left-side of Figure 6.1) as we described in Chapter 5. The second part was implemented to receive action commands from the framework and forward them to the robot to control joints and actuators (see right-side of Figure 6.1). A wizard was the third part of this setting. The wizard did nothing but inform the robot/framework whether the current task performed by either the robot or the participant was achieved successfully. The wizard was completely invisible to the participants, and the wizard had no impact on the robot's decision other than providing input regarding tasks' failure or success.

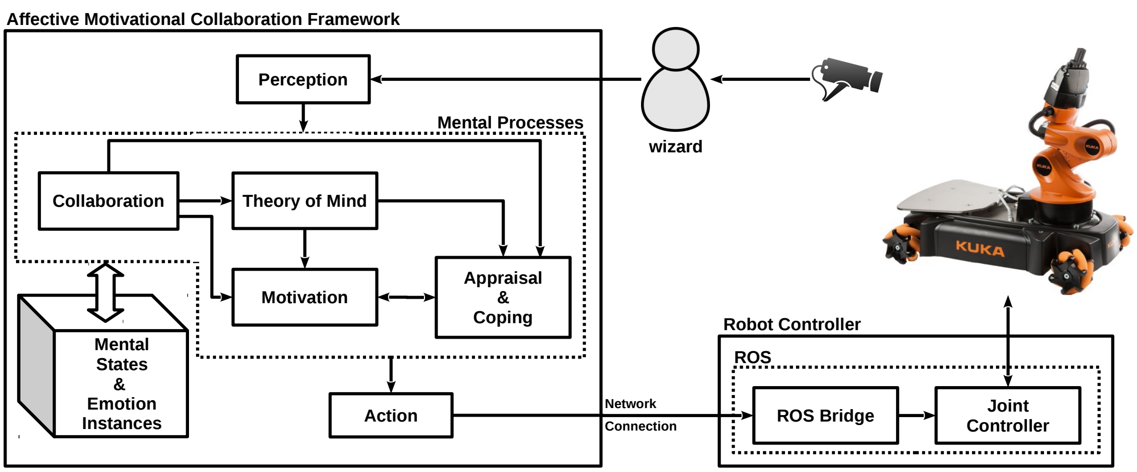

Figure 6.1: Computational framework based on Affective Motivational Collaboration theory (arrows indicate primary influences between mechanisms and data flow).

6.2.1 Framework

The framework includes all of the mechanisms depicted as mental processes in Figure 6.1 along with the mental states. The mental states shown in Figure 6.1 comprise the knowledge base required for all of the mechanisms in the overall model. The details about these mental processes and mental states are described in Chapters

3 and 5. In this user-study, the Collaboration mechanism uses a hierarchy of goals associated with tasks in the hierarchical task network structure depicted in Figure 6.2.

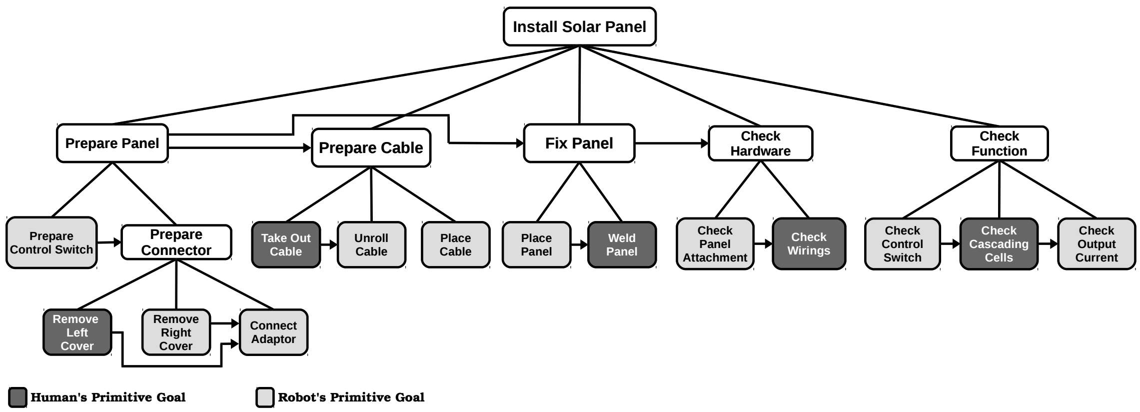

Figure 6.2: Collaboration structure used as the task model.

6.2.2 Robot Controller

The robot controller is comprised of two major components: 1) ROS-bridge and 2) joint controller (see Figure 6.1). ROS-bridge[1] provides an API to ROS functionality for non-ROS programs which enables us to send action commands from our framework (implemented in JAVA) to the robot's joint controller. The joint controller receives action commands and translates them into actual joint and actuator commands and sends them to the robot.

6.3 Experimental Scenario

Our scenario was based on a table top turn-taking game that we designed to simulate the installation of a solar panel. Participants collaborated one-on-one with our robot to complete all the given tasks required to install the solar panel. All of the tasks consisted of picking up and placing collaborators' available pegs on predefined spots on the board (see Figure 6.3). Each pick-and-place was associated with the robot's

[1] http://wiki.ros.org/rosbridge_suite

or the participant's task. The robot and the participants had their own unique primitive tasks that they had to accomplish in their own turns. 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.

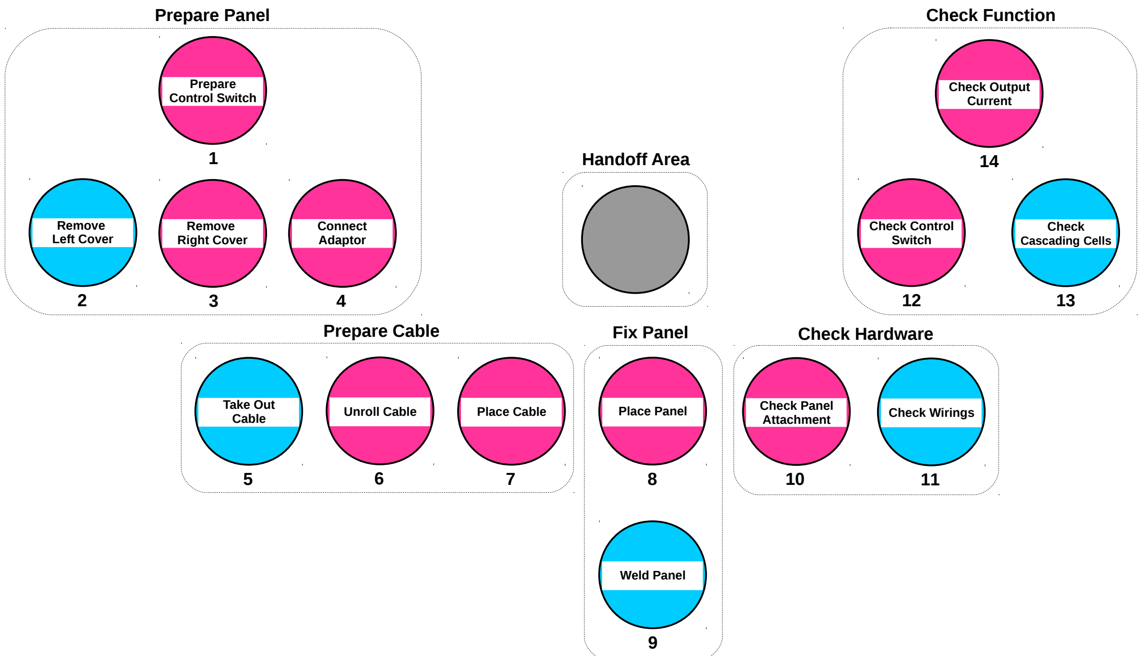

Figure 6.3: The layout of the available spots for the human and the robot to place their pegs during the collaboration.

6.3.1 The Robot

We conducted our experiment based on a KUKA Youbot (see Figure 6.5). The robot was stationary on top of a desk and was able to pick up and place available pegs corresponding to the robot's task. The robot was operated based on Robot Operating System (ROS – indigo) and was receiving commands through the ROS-bridge from our Affective Motivational Collaboration framework (see Figure 6.1). We provided a simple GUI using a touch-screen monitor (see Figure 6.4 and) to a) express the robot's positive, negative or neutral emotion through an emoticon, b) display the robot's utterances, c) control turn-taking process of the collaboration, and d)

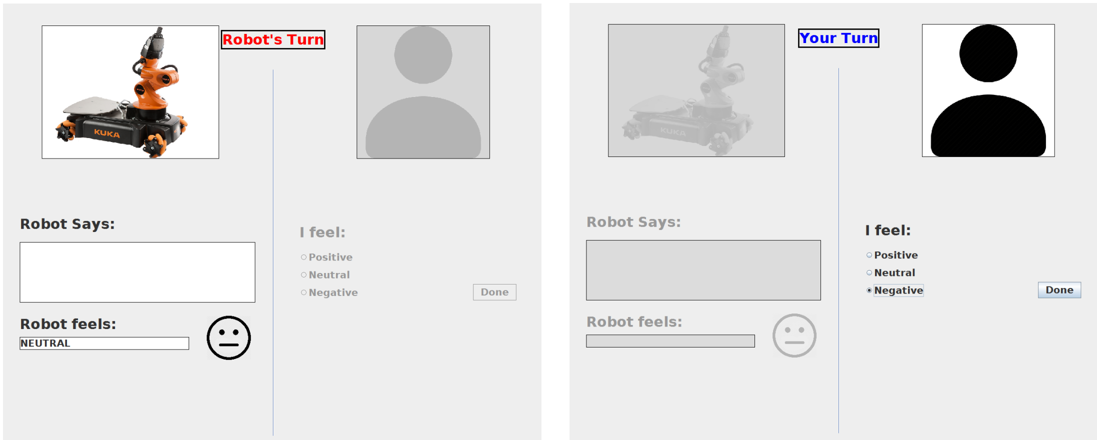

Figure 6.4: The Graphical User Interface (GUI) used during interaction.

let the participants express (report) their positive, negative or neutral emotion for each turn. The robot used MaryTTS an open-source, multilingual Text-to-Speech Synthesis platform to provide corresponding speech for its utterances in English.

6.3.2 Interaction Paradigms

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 working towards a new goal, the robot informed the participant about the higher level non-primitive goal (e.g. Prepare Panel – see Figure 6.2) of which the primitives were going to be working towards. The same procedure was used by the robot if there was a decision to switch to another nonprimitive due to the failure of a task in achieving the current goal. After achieving a new primitive goal, the robot either informed the human that it would pursue the next goal, or it informed and passed the turn to the human to execute the next task with respect 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 made a decision about which goal to pursue and informed the human accordingly. The same procedure was applied to both conditions.

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. There were two conditions of the robot: 1) emotion-aware and 2) emotion ignorant. The robot used neutral expression in the case of emotion-ignorance. The interaction was controlled autonomously by the framework we discussed in Section 6.2.1 in both the emotion-ignorant and the emotion-aware cases. 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 collaboration outside of the test area. The interaction was structured based on the exact same goals in the same HTN for both conditions. The robot was using the same utterances in both conditions. In the emotion-aware condition the robot used a different behavior in comparison with the emotion-ignorant condition only if the participant was expressing a negative emotion in the event of a failure; i.e., the robot's utterances were identical in emotion-ignorant and emotion-aware cases if in the latter the participant reported (expressed) a positive or a neutral emotion.

Three different behaviors could be generated only in the emotion-aware condition. These three behaviors were 1) mitigating the human's negative emotion and postponing its own task to help the human, 2) goal-management to switch to another goal which has lower cost with respect to the human's negative emotion, and 3) task delegation to the human to overcome the impasse. In each run, the human had two pre-coordinated task failures, and the robot had one. If the human expressed negative emotion after the first human task-failure, the robot responded by mitigating the human's negative emotion by saying "It was not your fault. I can help you with this task" and helping the human by providing a peg to fulfill the human's task. If the human expressed negative emotion after the second human task-failure, the robot informed the human that they could proceed with another task to save time while simultaneously requesting a new peg (i.e. help) from the supervisor. If the human expressed negative emotion as a result of the robot's task failure, the robot requested help from the human (who had the correct peg). In the event that the human expressed positive or neutral emotion during these three failures, the robot behaved identically in the emotion-ignorant and the emotion-aware cases, by asking the supervisor for help.

6.3.3 Environment and Tasks

The environment was set up in the Human-Robot Interaction lab and included the robot, the collaboration board on top of a desk, and the participant standing in front of the robot on the other side of the board (see Figure 6.5). One of the experimenters monitored the interactions using a live stream of a camera in a different room. The experimenter provided only the required perception, i.e., decision on success or failure of the tasks for the robot, through the entire time of the collaboration (see Section 6.3.2).

The tasks were defined based on the HTN structure shown in Figure 6.2 and were executed in a turn-taking fashion by either of the collaborators. For each task either the robot or the participant was responsible to pick up one of the corresponding pegs from their own inventory and place it on the right spot which was colored and tagged the same as the associated peg. Some pegs and corresponding spots on the board had hidden magnets which prevented the pegs from standing upright. Any peg that fell over was considered a failed task.

6.4 Evaluation

6.4.1 Hypothesis

The non/social functions of emotions impact a collaboration process. Human collaborators prefer to collaborate with others whose behaviors are influenced by these functions of emotions depending on the context. We developed seven hypotheses on positive influence of emotion-awareness and usefulness of emotion function during collaboration:

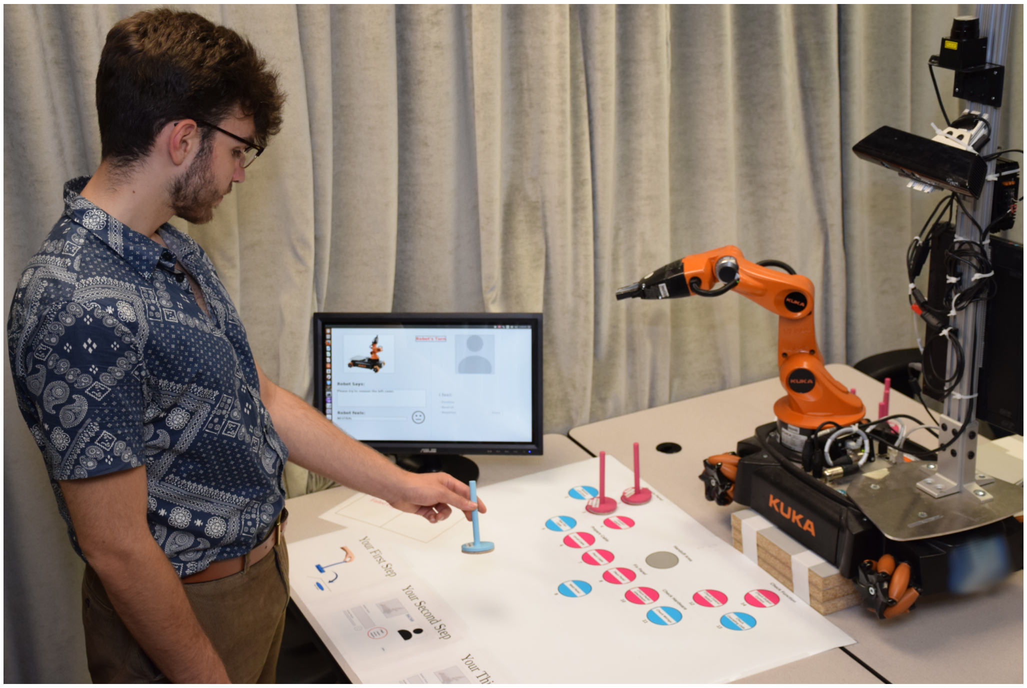

Figure 6.5: Experimental setup.

Hypothesis 1. Participants will feel closer to the emotion-aware robot rather than the emotion-ignorant robot.

Hypothesis 2. Participants will find the emotion-aware robot to be more trustworthy than the emotion-ignorant robot.

Hypothesis 3. Participants will find the emotion-aware robot to have better performance in collaboration than the emotion-ignorant robot.

Hypothesis 4. Participants will find the emotion-aware robot to be more understanding of their feelings than the emotion-ignorant robot.

Hypothesis 5. Participants will find the emotion-aware robot to be more understanding of their goals than the emotion-ignorant robot.

Hypothesis 6. Participants will feel more satisfied about the collaboration when working with the emotion-aware robot rather than emotion-ignorant robot.

Hypothesis 7. Participants will perceive higher level of mutual satisfaction with the emotion-aware robot than emotion-ignorant robot.

6.4.2 Procedure

Participants were first given a brief description of the purpose of the experiment. After the short introduction, they were asked to review and sign a consent form. Participants were then provided with a written instruction of their task and the rules for collaborating with the robot. Then, one of the experimenters lead them into the experiment room and asked the participants to asked to answer pre-experiment questionnaires. Afterwards, the experimenter went through all the details of the instructions with the participants standing in front of the collaboration board and the robot. The experimenter confirmed participants' correct understanding of the tasks and informed them of types of task failures that might occur during the collaboration. Participants were told that researchers were developing a collaborative robot and would like their help in evaluating their design. Participants were provided with identical instructions and randomly assigned to complete either the emotion-aware or the emotion ignorant condition first. They were told that, after their collaboration with the robot, they would be asked to answer a questionnaire on their experience. After completing the first round of collaboration, participants answered a post-experiment questionnaire that measured their perceptions of the robot, the task, and the collaboration procedure. After answering the first post-experiment questionnaire, participants were told that they were going to collaborate with the robot one more time and the robot might not necessarily have the same collaborative behavior. After completing the second round of collaboration, participants were asked to answer the second post-experiment questionnaire which consisted of the same questions as the first post-experiment questionnaire. After all, participants were asked to answer an open-ended questionnaire which measured their perception of difference between two runs, their preference of collaborative robot between two runs, and their reasons of preference.

6.4.3 Measurements

In our study two basic conditions of the robot were tested: a) the emotion-ignorant condition, b) the emotion-aware condition. We measured participants' recall of the collaborative behaviors presented by the robot using an open-ended post-experiment questionnaire. We also specifically asked the participants what behavior of the robot they liked during their collaboration. We also evaluated participants' levels of satisfaction, trust, goal achievement, mutual understanding of goals, mutual understanding of feelings, mutual agreement, and also participants' beliefs about the efficiency of collaboration and their feeling of robot's collaborative behaviors. Seven-point Likert scales were used in these questionnaire items.

6.4.4 Participants

A total of 37 participants participated in the experiment in 74 trials. Participants were recruited from Worcester Polytechnic Institute's students and staffs as well as other civilians recruited from outside of the campus. The ages of the participants varied between 19 and 74 with an average of 34.2 years before our screening of 4 participants based on our sanity check questions. After this screening the ages of the participants varied between 19 and 54 with an average of 30.8 years old. Of the 33 participants, 21 were female and 12 were male. Each participant participated in 2 trials. In one trial the robot was aware of human's emotion and in the second trial the robot was ignoring human's emotion. The order of these two trials were randomly assigned to each participant. In general we used emotion-ignorant robot first in 16 experiments, and emotion-aware robot first in 17 experiments.

6.5 Results

As discussed in Section 6.4.3, results of the user study were gathered through a 31-question Likert-scale survey that was given to each participant after each run with the robot, and through a 5-question open-ended summary questionnaire at the end of the experiment.

Question Category	Question	Question Number
Likability	I felt close to the robot.	Q1
	I would like to continue working with the robot.	Q2
	I like the robot.	Q3
	The robot was interesting.	Q4
Trust	I trust the robot.	Q5
	It was easy to express myself to the robot.	Q6
	I trust the robot to perform appropriately in our collaboration.	Q7
	I am confident in the robot's ability to help me.	Q8
	I trust the robot to assess my feelings appropriately in our collaboration.	Q9
Robot's Performance	The robot was repetitive.	Q10
	The robot made efficient decisions.	Q11
	The robot's decisions improved my performance during the collaboration.	Q12
Robot's Understanding of Human's Emotions	The robot understood my emotions.	Q13
	The robot is sometimes confused about what I feel about our activities.	Q14
	I feel that the robot, in its own unique ways, is genuinely concerned about me.	Q15
	The robot understands some of my feelings and takes them into account in our collaboration.	Q16
	The robot does not understand how I feel during our collaboration.	Q17
Robot's Understanding of Goals	The robot does not understand what we are trying to accomplish.	Q18
	The robot does not understand what I am trying to accomplish.	Q19
	The robot perceives accurately what my objectives are.	Q20
	The robot was committed to the collaboration.	Q21
Human Feeling about Collaboration	I find what the robot and I are doing is unrelated to my goals.	Q22
	I find what I am doing with the robot confusing.	Q23
	The robot and I are working towards mutually agreed-upon goals.	Q24
	The robot and I collaborate on setting goals for us to work on.	Q25
	The robot and I agree on what is important for us to work on.	Q26
	I believe that the robot and I achieved the goals we set.	Q27
	I am satisfied with the outcome of our collaboration.	Q28
Satisfaction of Collaborative Partner	The robot was satisfied with my collaborative behavior.	Q29
	I was satisfied with the robot.	Q30
	I understand the robot, and I think it understands me, at least in the best way it can.	Q31

Figure 6.6: The 31 Likert scale questions organized according to their groups.

6.5.1 7-Point Likert Scale Survey Results

As mentioned previously, the 7-point Likert scale survey was administered at the end of the emotion-ignorant run and at the end of the emotion-aware run for each

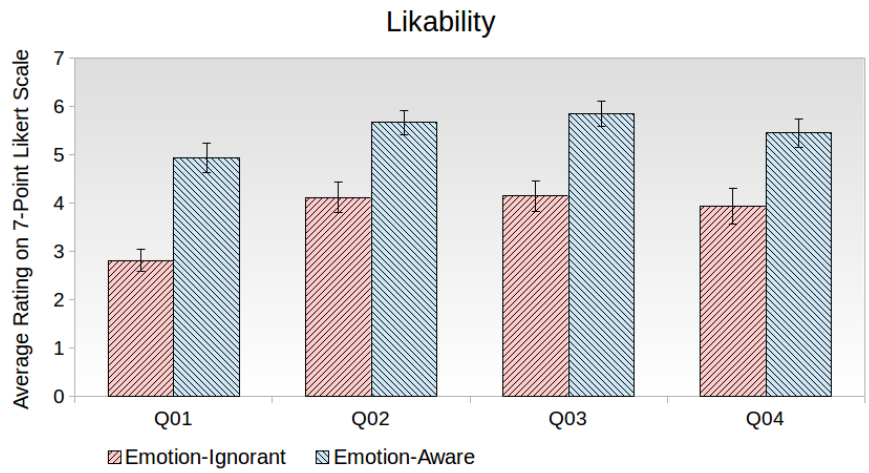

Figure 6.7: Results of the Likert scale survey for Likability questions. The p-value for the difference between means is $\ll$0.001 for all questions.

participant. The 31 questions are generally categorized to evaluate the humans' perceptions of the following seven categories, with 3-7 questions per group: (1) the likability of the robot (2) the level of trust the human feels in the robot (3) the human's perception of the robot's performance (4) the human's perception of the robot's understanding of human's emotions (5) the human's perception of the robot's understanding of human's and collaboration's goals and objectives (6) the human's feeling about the collaboration and (7) the human's perception of the human's and robot's mutual satisfaction with each other as collaborative partners. The questions presented are provided in Figure 6.6.

The results were analyzed using a two-tailed paired t-test to analyze the difference of means between the emotion ignorant and the emotion-aware condition. Refer to Figures 6.9 - 6.13 for the results. As mentioned in Section 6.4.4, participants were randomly assigned to complete either the emotion-ignorant or the emotion-aware run first; analysis of the results revealed no statistically significant difference or consistent pattern based on which run the participant completed first.

Likability of the Robot

Questions 1 through 4 addressed the likability of the robot. As shown in Figure 6.7, participants rated the emotion-aware robot 1.5-2.1 points higher than the emotion-ignorant robot. These results indicate that participants felt closer with and preferred working with the emotion-aware robot; these results support Hypothesis 1, which stated that humans would prefer to work with the emotion-aware robot over the emotion-ignorant robot.

Human Trust in the Robot

Questions 5-9 were designed to measure the degree of trust that the human participants felt in the robot. As shown in Figure 6.8, participants trusted the emotion-aware robot, on average, a minimum of 1.4 points more than the emotion-ignorant robot, both in general and in terms of collaboration performance. In Question 5, participants rated a general statement of trust 1.5 points higher in the emotion-aware case. Additionally, in Question 7, participants rated their trust in the emotion-aware robot to perform appropriately during collaboration an average of 5.9 on a 7-point Likert scale, where 7.0 would indicate maximum trust; this indicates an acceptable level of trust in the robot's collaborative abilities. These results support Hypothesis 2, that posits that human participants would find the emotion-aware robot to be more trustworthy than the emotion-ignorant robot.

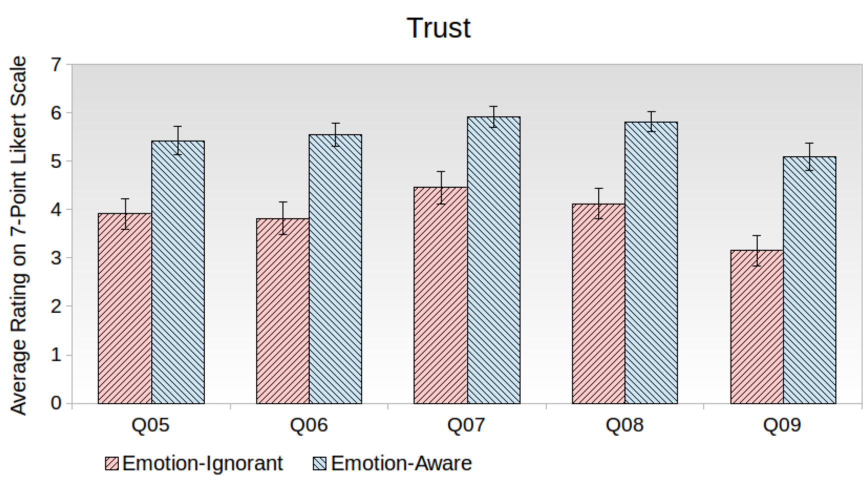

Figure 6.8: Results of the Likert scale survey for questions related to trust. The p-value for the difference between means is $\ll$0.001 for all questions.

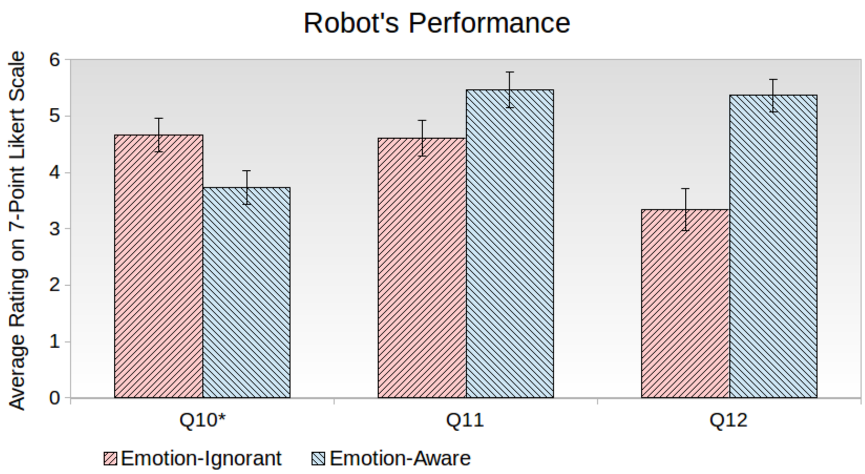

Figure 6.9: Results of the Likert scale survey for questions related to the robot's performance. The p-value for the difference between the means for questions 10, 11 and 12 are 0.001, 0.063 and $\ll$0.001, respectively.

Perception of the Robot's Performance

Question 10 (which is reverse-scored) measures the participant's perception of repetitiveness in the robot during the collaboration. In both conditions, participants rated the robot as moderately repetitive, with the emotion-ignorant robot's average response being about 1.1 points higher than the emotion-aware. This result correlates with several of the open-ended responses which described the emotion-aware robot's behaviors as "cute" and "interesting", refer to Section 6.5.2. Question 11, which asks about the efficiency of the robot's decisions is the only question of the 31 questions that did not have a statistically significant difference between the emotion-aware and the emotion-ignorant case. This correlates with the result of the open-ended question asking which condition of the robot exhibited behaviors that could prevent human error (refer to 6.5.2); in response to this question, several respondents stated that it may be quicker or simpler to call the supervisor in the event of a task failure, rather than changing the order of the tasks. According to the results from Question 12, the participants felt that the emotion-aware robot's decisions during collaboration improved their own performance, with an average rating of 5.4, while the emotion-ignorant robot only received an average rating of 3.3, indicating that participants felt it was not able to interact in such a way as to increase the human's performance; refer to results from Question 6. These results support Hypothesis 3, which posited that humans will perceive the emotion-aware robot as being more capable than the emotion-ignorant robot.

Robot's Understanding of Human Emotions

In Questions 13 through 17, participants evaluate the robot's understanding of humans' emotions. In questions 13, 15, and 16, participants rated the emotion-aware robot, on average, a minimum of 1.8 points higher than the emotion-ignorant robot. In response to questions 14 and 17, which are reverse-scored, participants ranked the emotion-ignorant robot 1.2 and 2.0 points higher, respectively, than then emotion-aware robot. The results of all five questions in this category support Hypothesis 4.

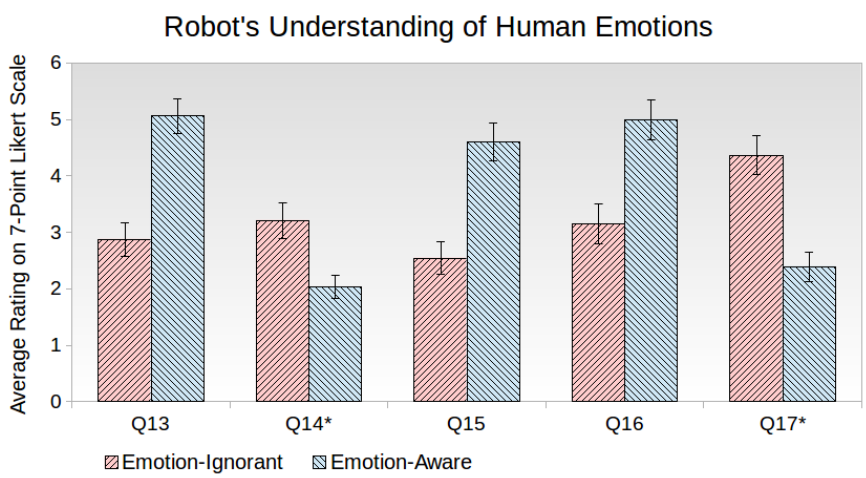

Figure 6.10: Results of the Likert scale survey for the questions related to the robot's understanding of human emotions. The p-value for the difference between the means is ≪0.001 for all of the questions except Question 14, for which the p-value is 0.003.

Robot's Understanding of Human and Collaboration Goals

Questions 18 and 19 were reverse-scored questions intended to determine whether the humans felt that the robot understood the shared collaboration goal and the human's personal goal, respectively. For both conditions of the robot, the average

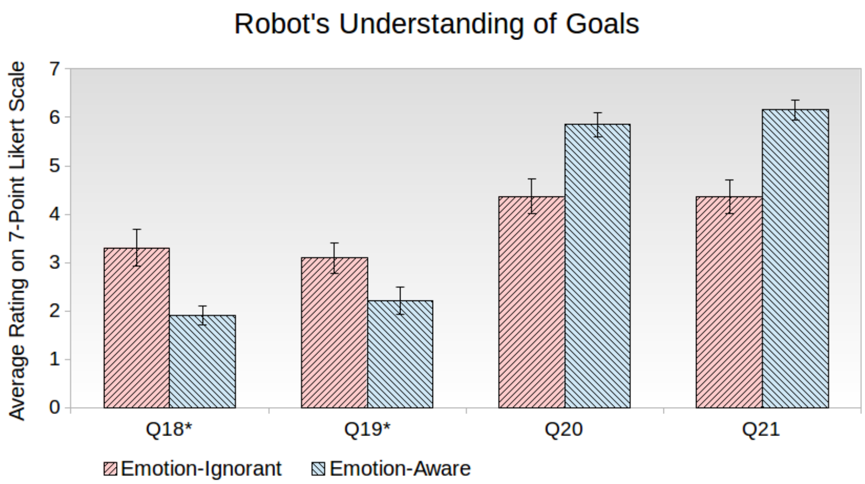

Figure 6.11: Results of the Likert scale survey for questions related to the robot's understanding of goals. The p-value for the difference between the means for all questions is $\ll$0.001, except Question 19, for which the p-value is 0.006.

scores were lower than 3.5, indicating that the human's perceived the robot as having some understanding of the goals. For both questions, the emotion-ignorant robot's average score was significantly higher than the emotion-aware robot's score. Similarly, Question 20 was a measure of whether the human perceived that the robot correctly perceived the human's goal. On average, participants provided an average rating for the emotion-aware robot that was 1.5 points higher than that for the emotion-ignorant robot. Question 21 measured the human perception of the robot's commitment to the collaboration; for this measure, the average participant score assigned to the emotion-aware robot was 6.2 points out of a maximum of 7 points, indicating that the participants felt that the emotion-aware robot was strongly committed to the collaboration. The emotion-ignorant robot received an average rating of 4.4 points, indicating only moderate commitment. These results strongly support Hypothesis 5, which posits that humans will feel that the emotion-aware robot will better understand their goals than the emotion-ignorant robot.

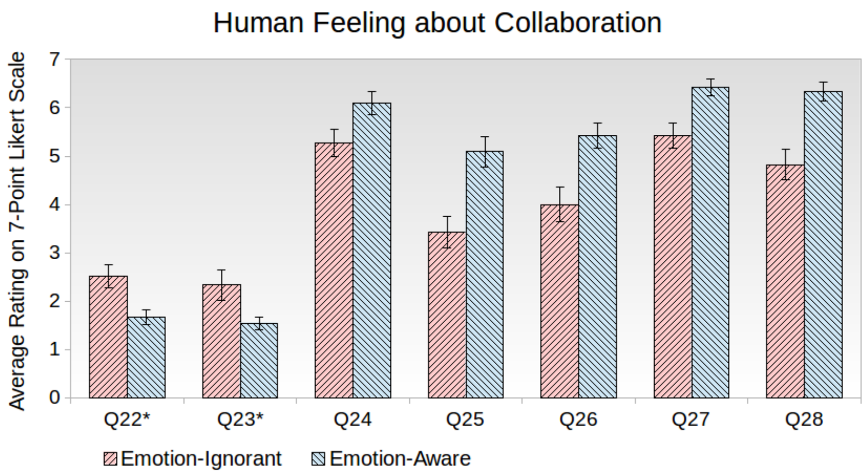

Figure 6.12: Results of the Likert scale survey for questions related to the human's feeling about the collaboration. The p-value for the difference between the means is ≪0.001 for questions 22, 25, 26, and 28. The p-value for Questions 23, 24 and 27 are 0.02, 0.008 and 0.001, respectively.

Human's Feeling about the Collaboration

Questions 22 through 28 were designed to gauge how the human participants felt about the partnership within the collaboration and the outcome of the collaboration. For each of the 7 questions, the participants ranked the emotion-aware robot as better than the emotion-ignorant robot, by a minimum, on average, of 0.8 points. Questions 24, 27 and 28 addressed whether the robot and the participant were working toward mutually agreed-upon goals and on the outcome of the collaboration; in the emotion-aware condition, participants rated the robot a minimum of 6.1 points, on average, while rating the emotion-ignorant robot 1-1.6 points lower, indicating that the participants felt a very strong sense of collaboration with the emotion-aware robot, and only a moderate sense of collaboration with the emotion-ignorant robot. Questions 25 and 26 address whether the robot and the participant set the collaboration goals together; these two questions have lower scores than Questions 24, 27 and 28, for both the emotion-aware and the emotion-ignorant case. The lower overall scores are likely due to the fact that the robot decides the task order or action in the event of failure in both conditions; however, the higher score in the

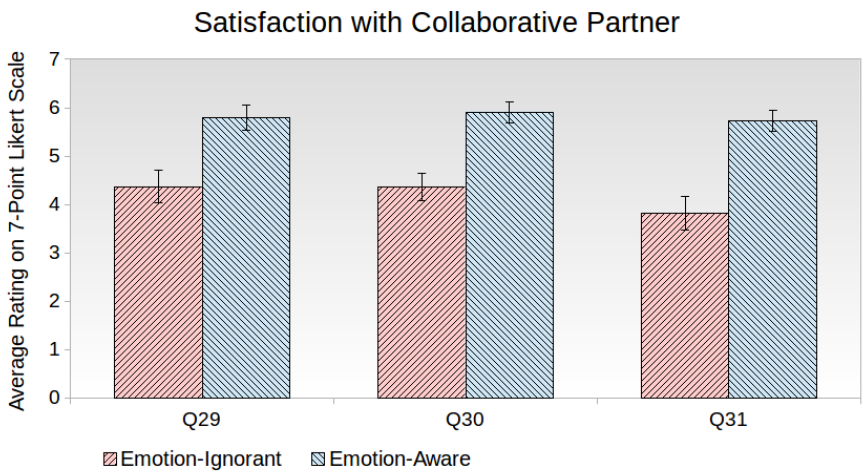

Figure 6.13: Results of the Likert scale survey for questions related to satisfaction with collaborative partner. The p-value for the difference between means is $\ll$0.001 for all questions.

emotion-aware case may indicate that emotional awareness can increase a feeling of collaboration. These results support Hypothesis 6 that humans will feel a greater sense of mutual collaboration and understanding about the collaboration with the emotion-aware robot.

Human Perception of Mutual Satisfaction with Collaborative Partner

Questions 29, 30 and 31 were designed to measure the human's perception of the robot's satisfaction with the human, the human's satisfaction with the robot and the mutual understanding between the human and the robot, respectively. The participants provided an average response in the emotion-aware condition of 5.8, 5.9 and 5.7 to Questions 29, 30 and 31, respectively, indicating a high level of mutual satisfaction; all three answers were about 1.4-1.9 points lower, on average, in the emotion-ignorant condition. These results indicate a higher level of satisfaction working with the robot in the emotion-aware condition, and strongly support Hypothesis 7, which posited that humans will feel a greater sense of mutual satisfaction with the emotion-aware robot than the emotion-ignorant robot.

6.5.2 Results from the Open-Ended Questionnaire

As described in Section 6.4.2, each participant answered an open-ended questionnaire at the end of the study. Figure 6.14 summarizes the questionnaire and which run users preferred for certain conditions (i.e. emotion-ignorant or emotion-aware). Note that some users chose not to state a preference regarding which run they preferred for certain conditions; because we were specifically interested in whether users preferred the emotion-aware case, we considered the ambiguous responses to be failures in the binomial analysis. The binomial analysis is based off of a population size of 33.

Question	Number of Participants Who Did Not Prefer One Run Over the Other *	Number of Participants Favoring Emotion-Aware Robot	*p*-value
Which of the two runs with the robot did you prefer?	0	33	0
In which of the two runs did the robot exhibit behavior that could be useful in a more complex task?	1	30	$\ll 0.001$
In which of two runs did the robot exhibit behavior that could prevent human error?	3	18	> 0.1
In which of the two runs did the robot exhibit behavior that could improve the efficiency of collaboration?	2	26	$\ll 0.001$
What was the most interesting behavior of the robot and in which run did it happen?	5	24	0.002

Figure 6.14: Open-ended questionnaire questions and results. (*Note: Because we are evaluating whether humans prefer an emotion-aware robot, these results are taken as negative test results when calculating the p-value using the binomial distribution. Only those participants who clearly indicated a preference for the emotion-aware robot are taken as positive test results.)

As shown in Figure 6.14, 100% of users unambiguously preferred the run with the emotion-aware robot. In general, this preference stemmed from a feeling of closeness and partnership, as seen in these responses: "the robot had emotions and responded to my emotions. Also, what it said about my failing was cute and aimed to make me feel better." Another example is "I liked feeling needed and accounted for; I felt closer to the robot." Finally, "I saw the changes in its feeling, which motivated me to care more about my act...I also liked that he asked me to correct its failure, although it could ask the supervisor."

When asked in which of the two runs the robot exhibited behavior that could be useful in a more complex task, 90.9% chose the emotion-aware robot. In general, respondents thought that the emotion-aware robot was better at problem solving, more adaptable, and more capable of handling the social complexities that occur in collaboration, as shown in responses such as “The robot explained motives...which is important to keep a team communicating and on the same pace.” Also, “When we failed he initially switched to a new task and then came back to the originally failed task. It kept me from getting irritated and negative.” Finally, “The more complex, the more necessary it is to understand how humans think and operate...an empathetic robot can adapt, encourage and help.” It is worth noting that one respondent preferred the emotion-ignorant case, saying “In a more complex task it might be better for the robot to take control and simply tell me what to do; trying to be understanding and collaborative wouldn’t be as important as doing the task correctly.”

The only question that did not provide statistically significant support in favor of the emotion-aware robot related to which case the robot exhibited behavior that could prevent human error. About 36.4% of respondents thought that the emotion-ignorant robot was more likely to prevent human error; however, all but one of these cited calling the supervisor as the main method of preventing human error, in spite of the fact that the instructions indicated that the robot’s need to call the supervisor counted against the collaboration. Of the 54.5% who thought that the emotion-aware robot was better at preventing human error, most cited the robot’s ability to console the human as the main behavior that could prevent human error. Respondents indicated that this enabled them to move on and feel better about the collaboration, as with this response: “The robot switched to a different task and we came back to an error later. This allowed my mind to move away from being frustrated. I was able to complete a different task which felt like a win - then come back and finish the error. Making my mind move away from frustration could definitely prevent more errors.”

When asked in which of the runs the robot exhibited behavior that could improve the efficiency of the collaboration, 78.8% responded with the emotion-aware case; of these, the vast majority stated that this was because of the robot's ability to change the order of tasks in the event of a failure, and to ask the human for help.

Finally, when asked in which run the most interesting behavior occurred, 72.7% chose the emotion-aware condition. Of these respondents, 12 individuals stated that the robot's attempt to console the human by saying "It was not your fault" in response to the human's negative emotion that occurred as a consequence of the human's failed task was the most interesting behavior, and a majority mentioned that it actually made them feel more positive. Six participants referred to the robot's ability to understand and express emotion. Several participants referred to the robot's ability to communicate, including the ability to ask questions. Of those who responded with the emotion-ignorant case, most found the ability to call the supervisor, and mechanical functions, such as gripping, to be most interesting.

6.5.3 Impact of Demographics

As mentioned in Section 6.4.4, we recorded certain demographic information from each participant, including age and gender. We also had each participant complete several personality questionnaires. Although it was not the primary purpose of the study, we investigated the Likert scale results to determine if there were any relevant trends based on the demographics and personalities of the participants. A close study of the results did not reveal any identifiable pattern based on gender or personality.

Age did reveal an interesting pattern. We divided the participants into two groups, below 30 years of age and 30 or above. While question-by-question comparisons revealed only a few statistically significant differences based on age, a general pattern emerged. For all but four of the 31 questions presented, the younger age group reported higher scores than the older age group (or lower, in the case of reverse-scored questions)for the emotion-aware robot. In the emotion-ignorant case, the younger group tends to score the robot nearer to the same value as the older age group for all but seven questions, leading to a pattern in which the score drop

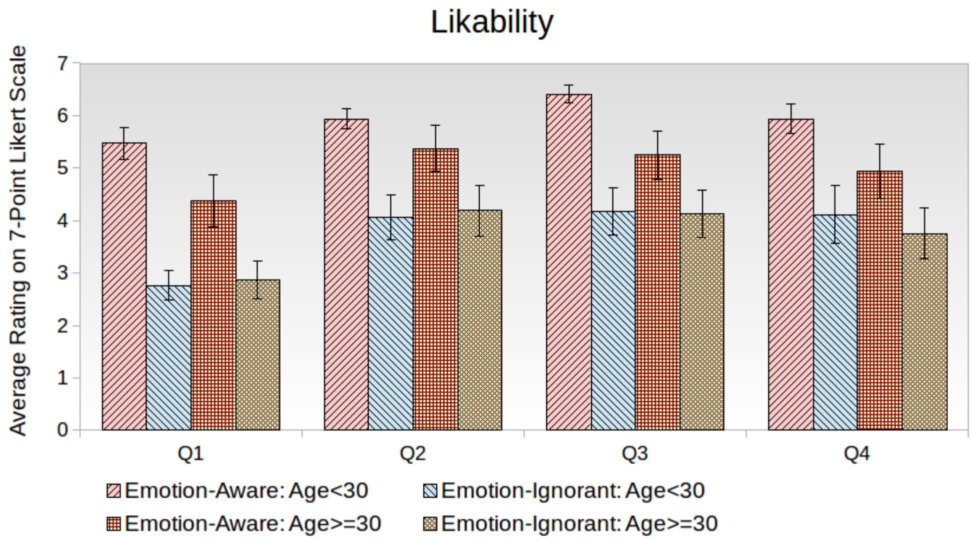

Figure 6.15: Impact of age on results of Likert scale questions related to likability.

between the emotion-aware and the emotion-ignorant case was more for the younger group than for the older group; the seven questions that broke this pattern were 7, 9, 11, 12, 18, 19 and 22.

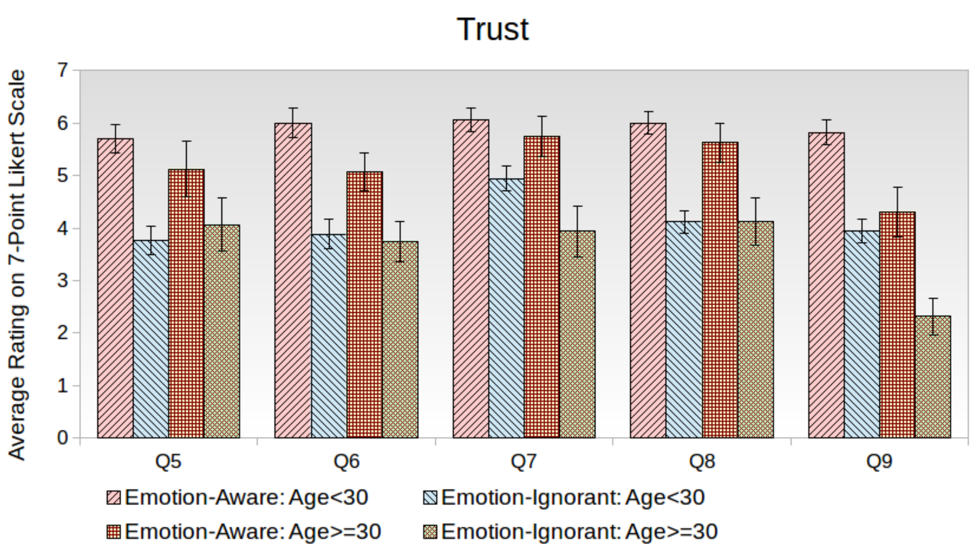

Figure 6.16: Impact of age on results of Likert scale questions related to trust.

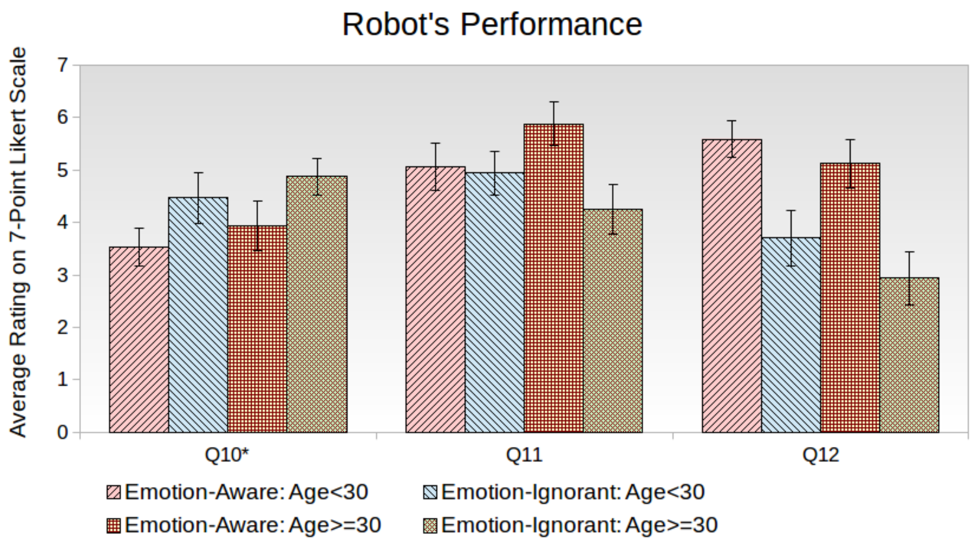

Figure 6.17: Impact of age on results of Likert scale questions related to performance.

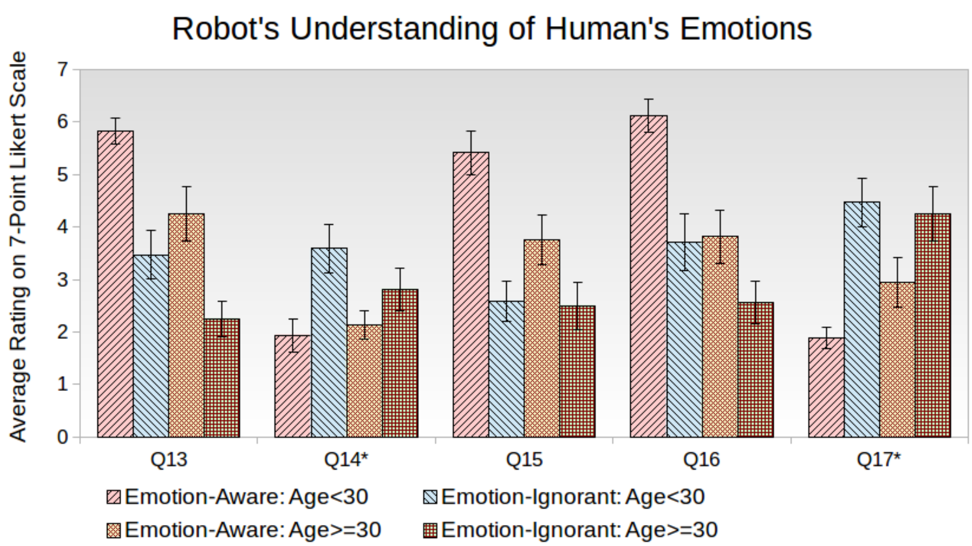

Figure 6.18: Impact of age on results of Likert scale questions related to robot's understanding of human's emotions.

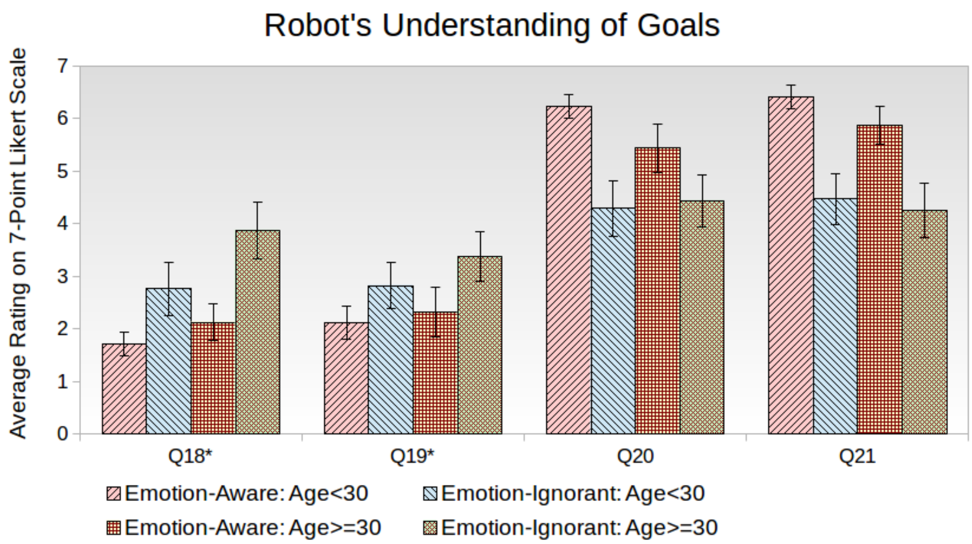

Figure 6.19: Impact of age on results of Likert scale questions related to robot's understanding of goals.

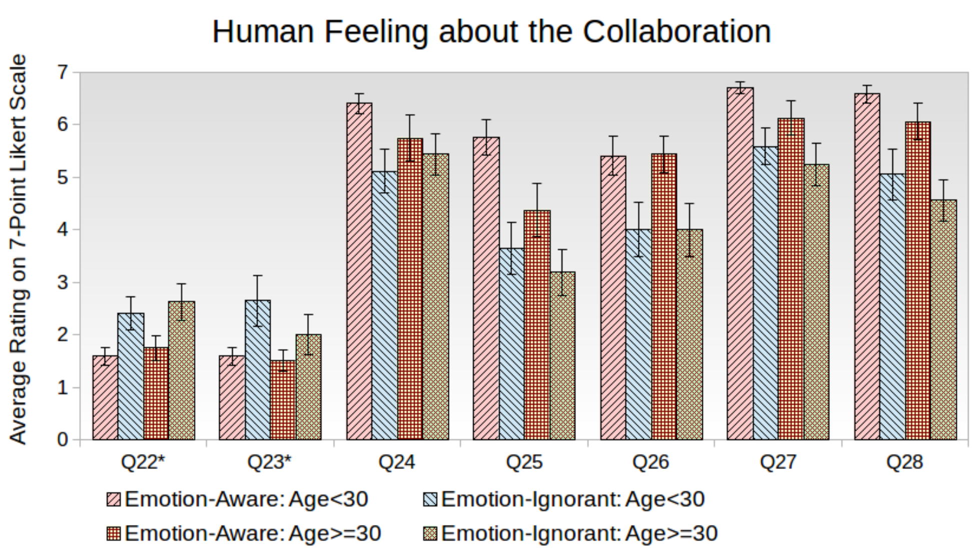

Figure 6.20: Impact of age on results of Likert scale questions related to human's feeling about collaboration.

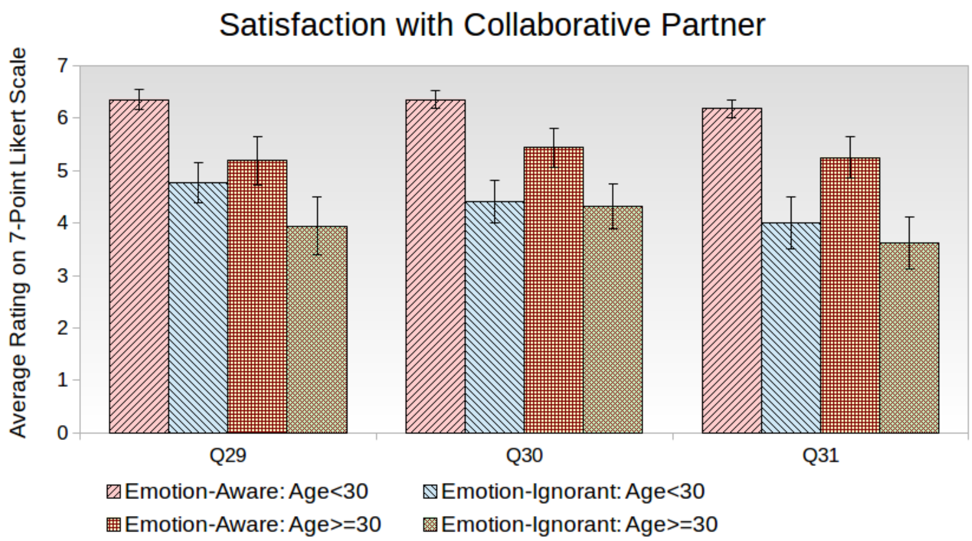

Figure 6.21: Impact of age on results of Likert scale questions related to satisfaction with collaborative partner.

6.6 Discussion

Based on the results, all participants prefer to work with the emotion-aware robot. Humans find the emotion-aware robot more likable and more trustworthy, as indicated in the Likert-scale responses and the open-ended questionnaire responses. Based on the responses, the emotional interaction with the robot can help create a sense of closeness and enjoyment that makes humans want to continue working with the robot.

The results also indicate that the emotion aware robot can better maintain a collaborative relationship. Both Likert-scale responses and Open-Ended Questionnaire responses indicate this. Humans felt a stronger sense of the robot's commitment to the collaboration, and greater understanding of their goals and emotions from the robot. Several open-ended responses also indicated that the robot was able to successfully motivate people and maintain their commitment to the collaboration, especially when tasks failed. Additionally, as shown in Section 6.5.1, humans rated the emotion-aware case much higher than the emotion-ignorant case when asked which robot's decisions improved their performance, in essence acknowledging that their collaborator's (i.e. the robot's) decisions had a significant impact on their performance. As some of the open-ended responses indicated, successfully managing emotions within the collaboration can help keep the collaboration on track, and prevent distractions due to guilt and other negative emotions.

Finally, the emotion-aware robot developed a stronger sense of partnership through greater communication. The participants felt better understood by the emotion-aware robot, and felt that the goals were more mutually agreed-upon, refer to Section 6.5.1. As evidenced in the following response, the emotion-aware robot was successfully able to create a sense of partnership through its more open communication style: "Communication is very important. In the first run (i.e. emotion-aware) the robot states what tasks he is working on, it is clear and straight-forward. Also during the first run the robot cares about the human(me)'s feelings and cheers me up when I failed at the tasks, I think that could also improve efficiency of collaboration, because it would be more like a team or partnership."

CHAPTER 7

CONCLUSION

7.1 Discussion

7.2 Future Work

BIBLIOGRAPHY

[1] M. E. Bratman. *Intention, Plans, and Practical Reason.* Cambridge, Mass.: Harvard University Press, 1987.

[2] C. Breazeal, A. Brooks, J. Gray, G. Hoffman, C. Kidd, H. Lee, J. Lieberman, A. Lockerd, and D. Mulanda. Humanoid robots as cooperative partners for people. *Journal of Humanoid Robots*, 1(2):1–34, 2004.

[3] C. Breazeal, A. Takanishi, and T. Kobayashi. *Social Robots that Interact with People*, pages 1349–1369. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008.

[4] P. Cohen and H. J. Levesque. *Teamwork.* SRI International, 1991.

[5] C. L. Dancy. ACT-Rϕ: A cognitive architecture with physiology and affect. *Biologically Inspired Cognitive Architectures*, 6:40–45, 2013.

[6] E. Goffman. *The Presentation of Self in Everyday Life.* Anchor, 1959.

[7] J. Gratch and S. C. Marsella. A domain-independent framework for modeling emotion. *Cognitive Systems Research*, 5(4):269–306, 2004.

[8] B. J. Grosz, L. Hunsberger, and S. Kraus. Planning and acting together. *AI Magazine*, 20(4):23–34, 1999.

[9] B. J. Grosz and S. Kraus. Collaborative plans for complex group action. *Artificial Intelligence*, 86(2):269–357, 1996.

[10] B. J. Grosz and C. L. Sidner. Plans for discourse. In P. R. Cohen, J. Morgan, and M. E. Pollack, editors, *Intentions in Communication*, pages 417–444. MIT Press, Cambridge, MA, 1990.

[11] C. L. John Robert Anderson. *The Atomic Components of Thought*. Lawrence Erlbaum Associates, 1998.

[12] J. Laird. *The Soar Cognitive Architecture*. MIT Press, 2012.

[13] N. Lesh, C. Rich, and C. L. Sidner. Collaborating with focused and unfocused users under imperfect communication. In M. Bauer, P. J. Gmytrasiewicz, and J. Vassileva, editors, *User Modeling 2001*, volume 2109, pages 64–73. Springer Berlin Heidelberg, 2001.

[14] D. J. Litman and J. F. Allen. Discourse processing and commonsense plans. In P. R. Cohen, J. Morgan, and M. E. Pollack, editors, *Intentions in Communication*, pages 365–388. MIT Press, Cambridge, MA, 1990.

[15] C. Marinetti, P. Moore, P. Lucas, and B. Parkinson. Emotions in social interactions: Unfolding emotional experience. In *Emotion-Oriented Systems, Cognitive Technologies*, pages 31–46. Springer Berlin Heidelberg, 2011.

[16] R. P. Marinier III, J. E. Laird, and R. L. Lewis. A computational unification of cognitive behavior and emotion. *Cognitive System Research*, 10(1):48–69, March 2009.

[17] S. C. Marsella and J. Gratch. EMA: A process model of appraisal dynamics. *Cognitive Systems Research*, 10(1):70–90, March 2009.

[18] V. Montreuil, A. Clodic, M. Ransan, and R. Alami. Planning human centered robot activities. In *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, pages 2618–2623, 2007.

[19] S. Planalp. *Communicating Emotion: Social, Moral, and Cultural Processes.* Cambridge University Press, 1999.

[20] K. R. Scherer, A. Schorr, and T. Johnstone. *Appraisal Processes in Emotion: Theory, Methods, Research.* Oxford University Press, 2001.

[21] C. L. Sidner and M. Dzikovska. A first experiment in engagement for human-robot interaction in hosting activities. In *Advances in Natural Multimodal Dialogue Systems*, volume 30 of *Cognitive Technologies*, pages 55–76. Springer Netherlands, 2005.

[22] Suppressed for Anonymity. 2016.

[23] S. van Hooft. Scheler on sharing emotions. *Philosophy Today*, 38(1):18–28, 1994.

[24] J. Yen, J. Yin, T. R. Ioerger, M. S. Miller, D. Xu, and R. A. Volz. Cast: Collaborative agents for simulating teamwork. In *Proceedings of IJCAI2001*, pages 1135–1142, 2001.

APPENDIX A