Affective Motivational Collaboration Theory

by

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ABSTRACT

Abstract Here!

ACKNOWLEDGMENTS

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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 [8]. 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] [8] [11], and are derived from Bratman's BDI architecture [1]. Two theories, Joint Intentions

[4] and SharedPlans [6, 7, 8], have been used to support teamwork and collaboration between humans and robots or virtual agents [2] [14] [16] [17]. 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 [10] and ACT-R [9], each with different approaches to defining the basic cognitive and perceptual operations. There have also been efforts to integrate affect into these architectures [5, 12]. 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 [8] 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 [8] and cognitive appraisal theory of emotions [13] [15], 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

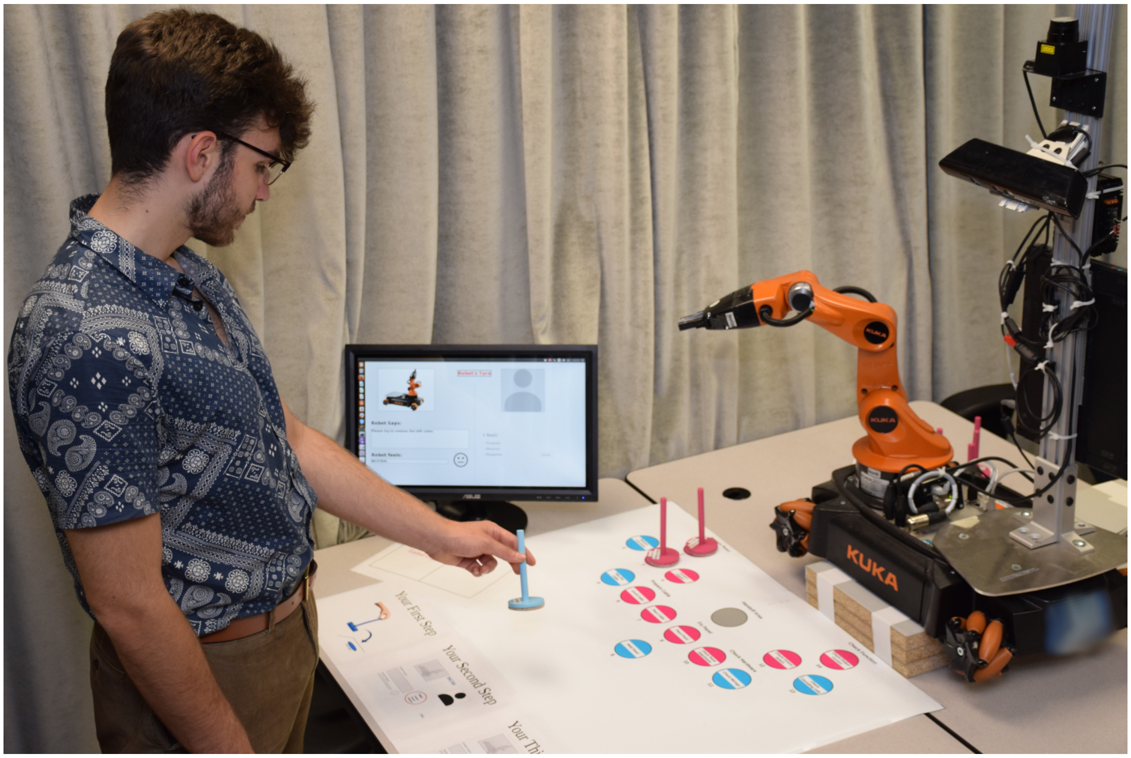

Figure 1.1: A robotic arm collaborating with a human to achieve a shared goal using *Affective Motivational Collaboration Framework*.

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 human subjects 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

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CHAPTER 3

AFFECTIVE MOTIVATIONAL COLLABORATION THEORY

3.1 Introduction

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CHAPTER 4
APPRAISAL PROCESSES IN COLLABORATION CONTEXT

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4.3.1 Relevance

4.3.2 Desirability

4.3.3 Expectedness

4.3.4 Controllability

4.4 Methodology [This chapter will contain the crowdsourding study.]

4.5 Results and Evaluation

We conducted a 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.

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 questionnaires, 14 questions (including 2 test questions) in the desirability questionnaire, and 22 questions (including 3 test questions) in the relevance questionnaire. Each subject group originally had 40 subjects. We limited the subject 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 subjects providing wrong answers to our sanity questions, and subjects with answering times less than 2 minutes. The final number of accepted subjects in each group is provided in Table 4.1.

Table 4.1: Evaluation Results

appraisal variables	# of subjects	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

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. We provided textual and graphical instructions for both questionnaires; Fig. 4.1 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, Mary, 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

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

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 Fig. 4.2), because we did not want to force subjects 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 ??). The questions were randomly placed in the questionnaire. Fig. 4.2 shows an example question from the relevance questionnaire which was designed to test whether human subjects perceive saliency as a factor in relevance. The input for our algorithms was the task model depicted in Fig. 4.1.

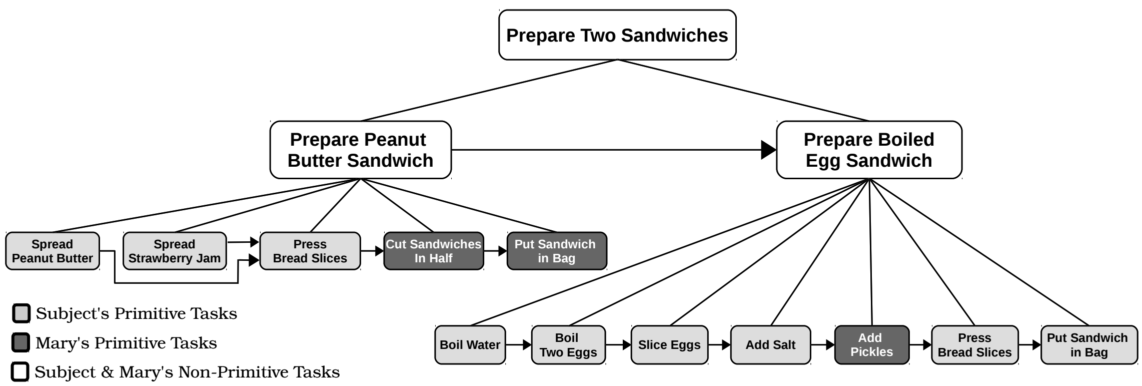

Figure 4.1: Collaboration Task Model for the Evaluation.

Average results and standard deviation of the fractions of subjects' 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 human subjects decisions and the output of our algorithms is significantly higher than 33%. The total number of subjects' 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 subjects 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 subjects' 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.

> 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 4.2: Example Expectedness Question.

Each question was designed based on different factors that we use in our algorithms (see Section **??**). 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 Fig. 4.1.

Fig. 4.2 shows the example question from the expectedness questionnaire. In this example, with respect to Algorithm **??** (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 Fig. 4.1). Although the task in option B is part of 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 human subjects will similarly differentiate between these two options. This question was presented to the human subjects 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 4.3: Example Controllability Question.

Fig. 4.3 shows an example question from the controllability questionnaire. The algorithm's output is option B, and is determined by Algorithm **??** (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 **??**) 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.

Fig. 4.4 shows an example question from the desirability questionnaire. The output based on the Algorithm **??** (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 4.4: Example Desirability Question.

In the example shown in Fig. 4.5, with respect to Algorithm **??**, option A is relevant because of Mary's perceived negative emotion (see Equation **??**). Although option B is relevant (since it achieves the next goal in the shared plan), 83% of subjects 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 subjects chose the option that accomplished the next goal in the shared plan. Interestingly, when confronted with a negative emotion from their collaborator, human subjects 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 human subjects chose the more salient option with respect to our definition of saliency, which was not referenced or provided in the questionnaire.

> 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 4.5: Example Relevance Question.

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

CHAPTER 5

COMPUTATIONAL FRAMEWORK

5.1 System Overview

5.2 Components of the Architecture

5.2.1 Mental States

5.2.2 Collaboration

5.2.3 Appraisal

5.2.4 Coping

5.2.5 Motivation

5.2.6 Theory of Mind

5.2.7 Perception

5.2.8 Action

CHAPTER 6
IMPROVING HUMAN-ROBOT COLLABORATION USING EMOTIONAL-AWARENESS

6.1 Introduction

As it was 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 Collaborative Behaviors and Emotional-Awareness

6.2.1 Goal Postponement

6.2.2 Goal Management

6.2.3 Task Delegation

6.3 Implementation

The implementation of this user-study included three separated 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). Finally, a wizard was the third part of this setting. The wizard did not do anything but informing the robot/framework whether the current performed task by either of the robot or the participant was achieved successfully. The act of the wizard was completely invisible for the participants, and the wizard had not impact on robot's decision other than providing tasks' failure or success.

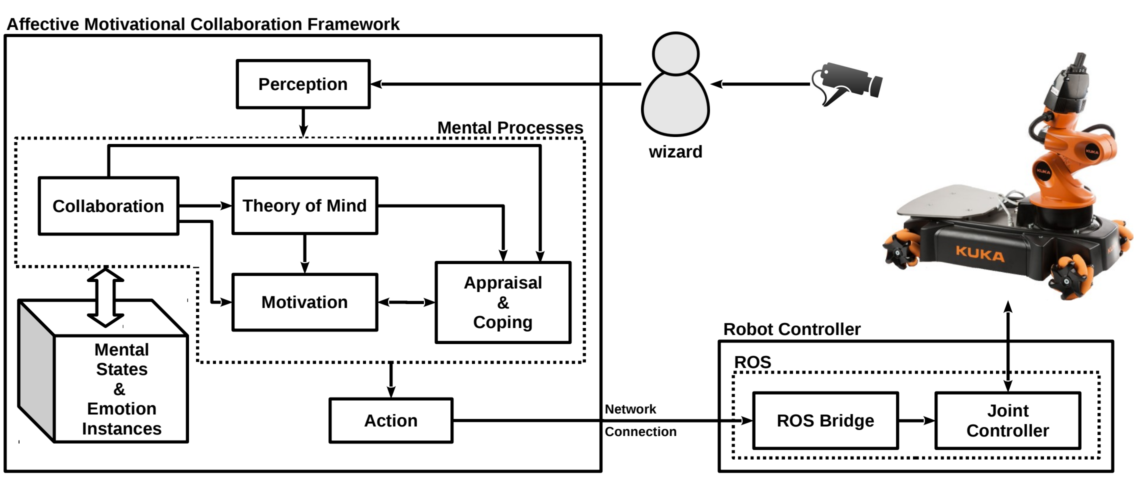

Figure 6.1: Computational framework based on [title suppressed for anonymity] theory (arrows indicate primary influences between mechanisms and data flow).

6.3.1 Framework

The framework includes all 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 a hierarchical task network structure depicted in Figure 6.2.

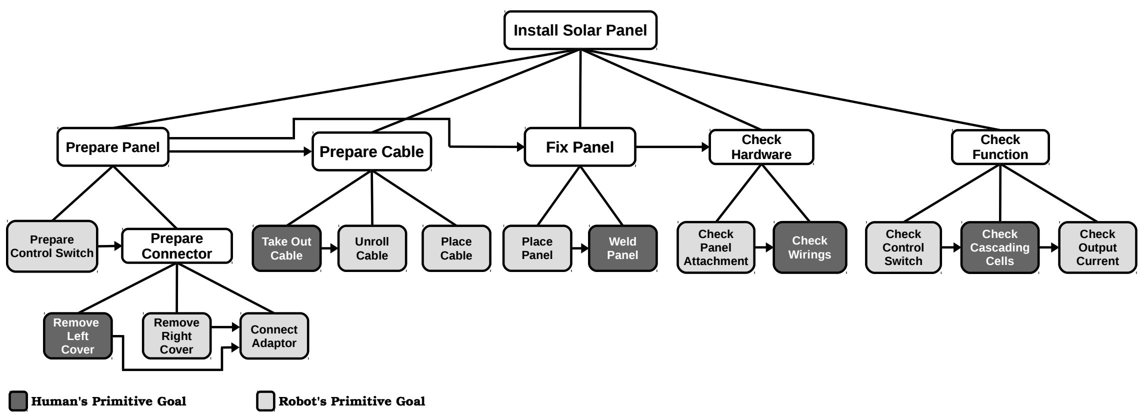

Figure 6.2: Collaboration structure used as the task model.

6.3.2 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.

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

6.4 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 had to collaborate one-on-one with our robot to complete all the given tasks required to install the solar panel. All 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 or the participant's task. The robot and the participants had their own unique primitive tasks that they had to accomplish in their own turn. The final goal of installing a solar panel required the robot and the participants to accomplish their own individual tasks. Failure of any task could create an impasse during the collaboration.

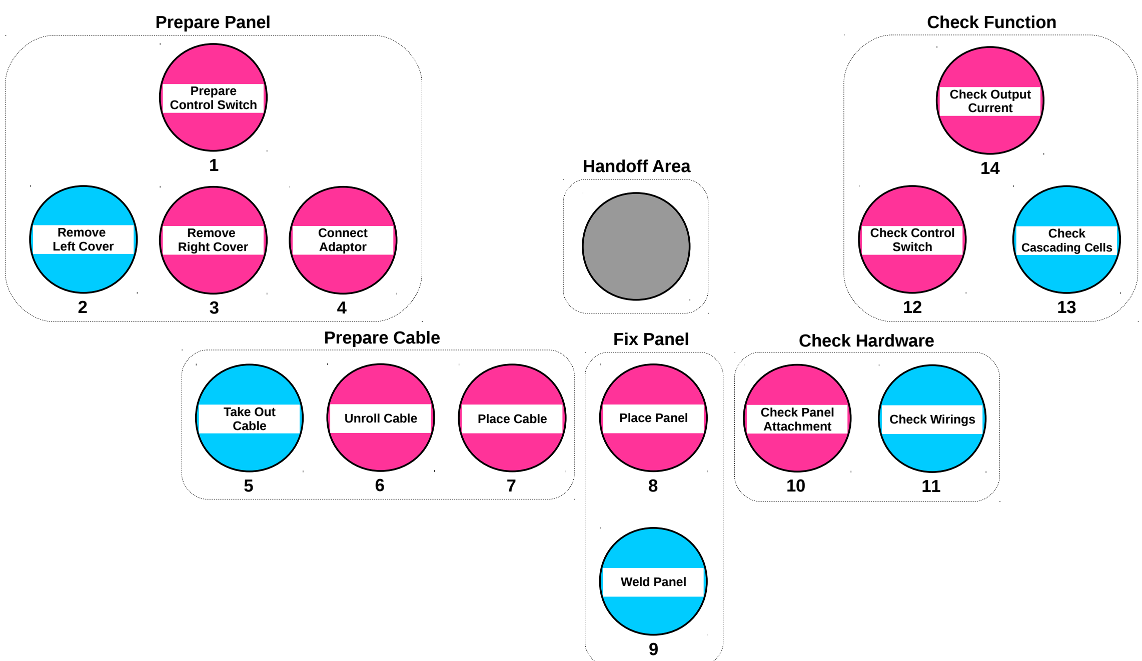

Figure 6.3: The layout of the available spots for the human and the robot to place their pegs during the collaboration.

6.4.1 The Robot

We conducted our experiment based on a KUKA Youbot (see Figure 6.6). The robot was stationary on top of a desk and was able to pick up and place avaiable pegs corresponding to the robot's task. The robot was operated based on Robot Operating System (ROS – indigo) and was receiving commands through the ROS-bridge from our [Title Suppressed For Anonymity] framework (see Figure 6.1). We used a touch-screen monitor providing a simple GUI (see Figures 6.4 and 6.5) to a) express robot's positive, negative or neutral emotion through an emoticon, b) display robot's utterances, c) control turn-taking process of the collaboration, and d) 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.

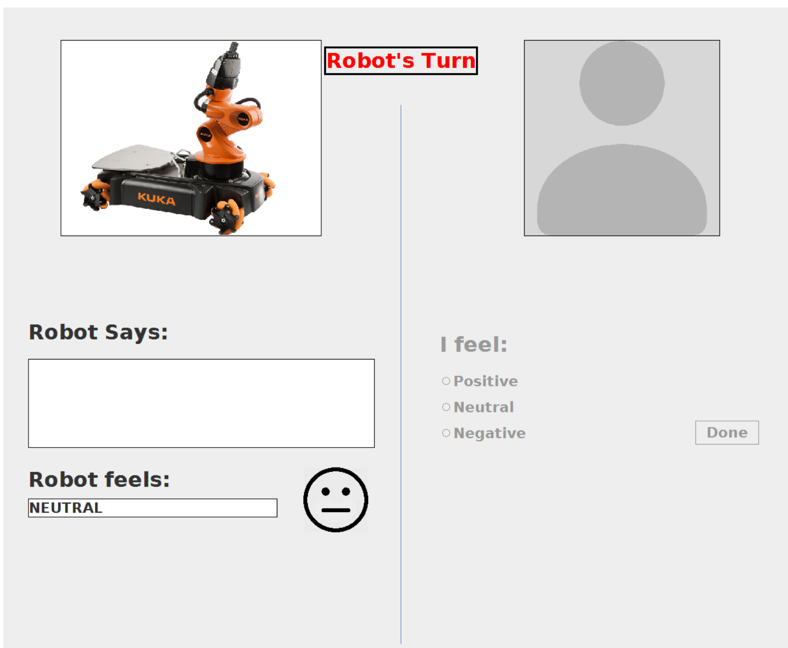

Figure 6.4: The GUI's look during the robot's turn.

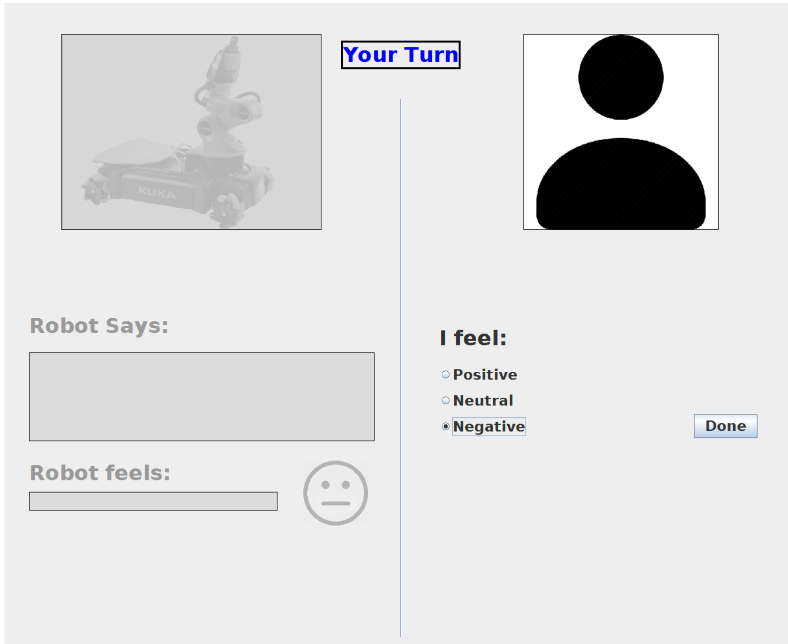

Figure 6.5: The GUI's look during the human's turn.

6.4.2 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 4.1) 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 6.3.1 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 an 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 case of a failure; i.e., the robot's utterances were identical in emotion-aware and emotion-ignorant 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.

6.4.3 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 6.6). 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 6.4.2).

The tasks were defined based on the HTN structure shown in Figure 4.1 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 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.

6.5 Evaluation

6.5.1 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:

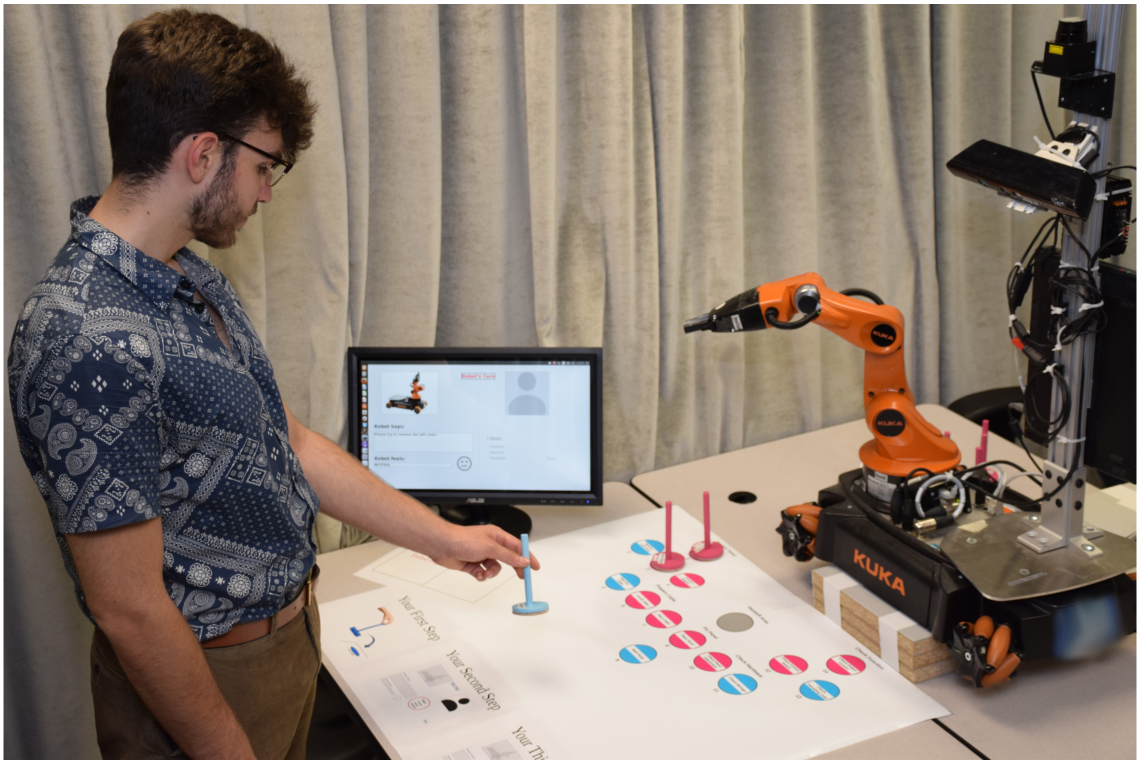

Figure 6.6: Experimental setup.

Hypothesis 1. Subjects will feel closer (likability) to the emotion-aware robot rather than the emotion-ignorant robot.

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

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

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

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

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

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

6.5.2 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 the conditions in the experiment. 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.

6.5.3 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, confusion, 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.

6.5.4 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 subjects 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.

6.6 Results

As discussed in Section 6.5.3, 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

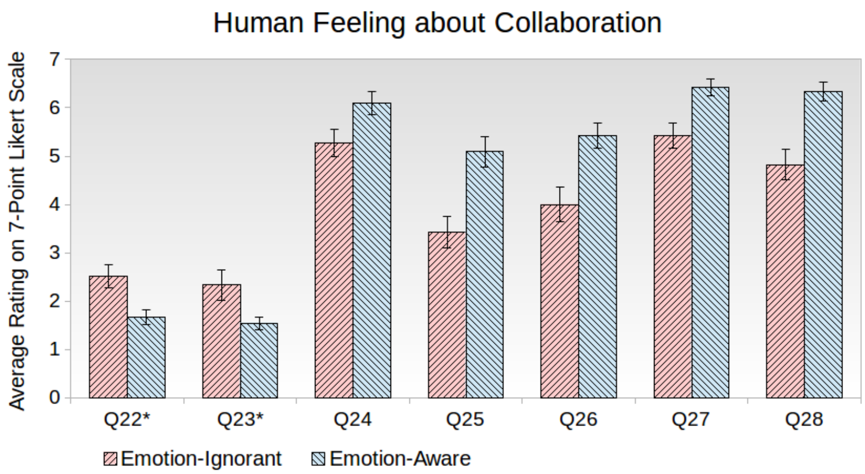

Figure 6.7: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

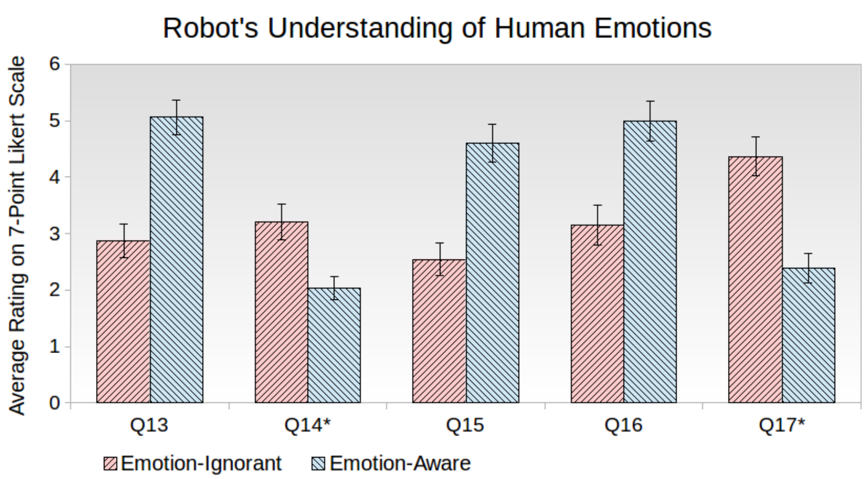

Figure 6.8: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

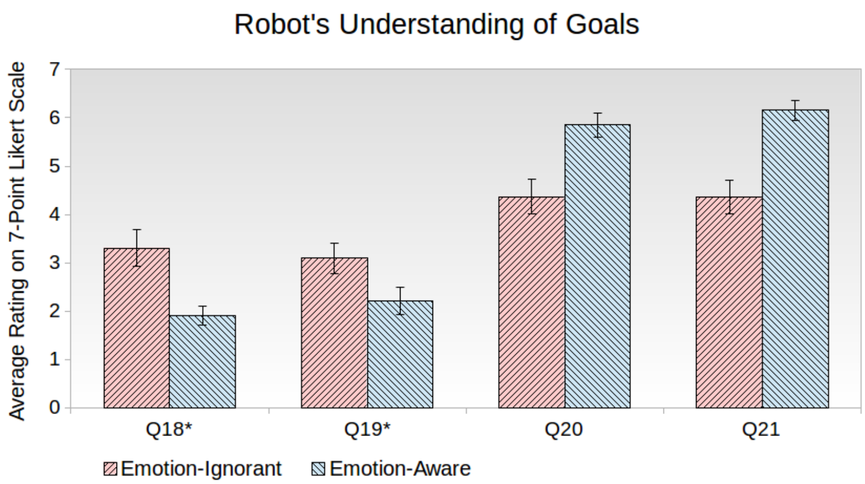

Figure 6.9: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

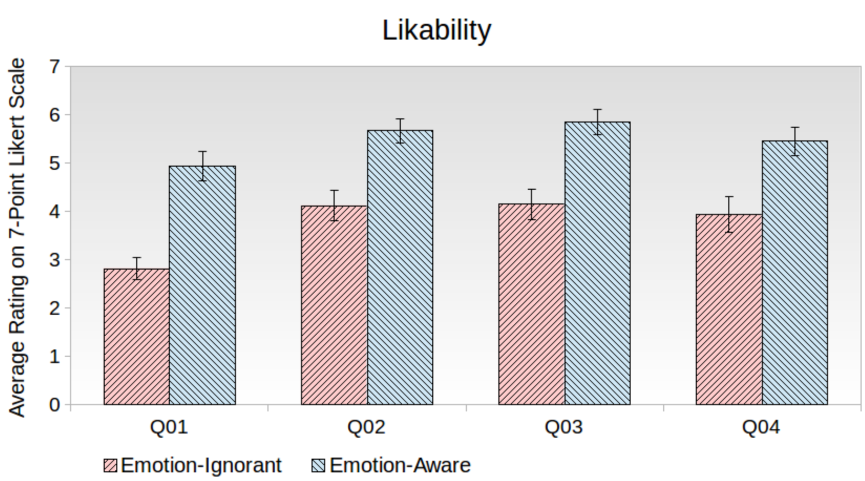

Figure 6.10: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

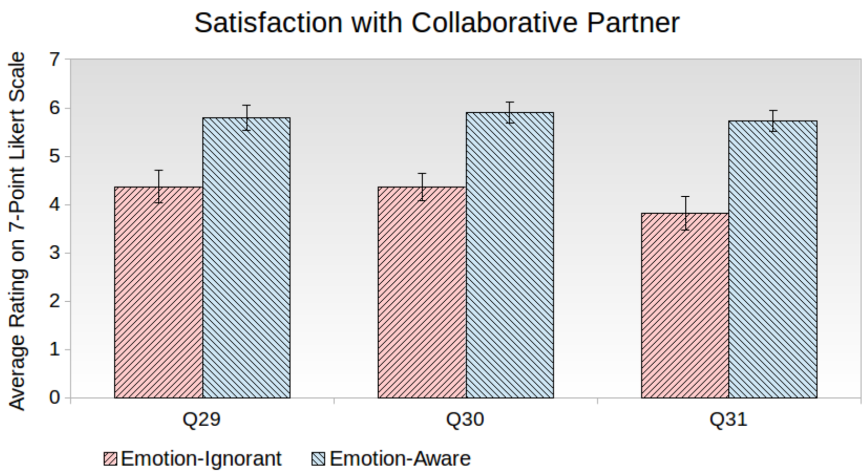

Figure 6.11: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

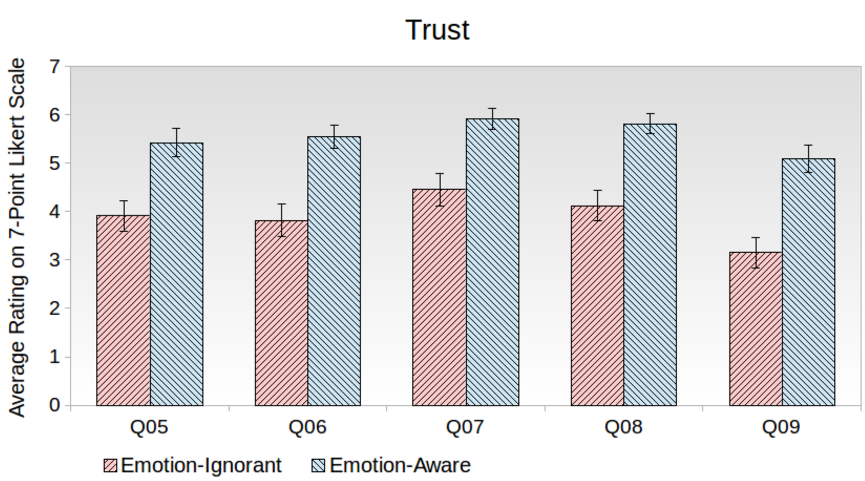

Figure 6.12: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

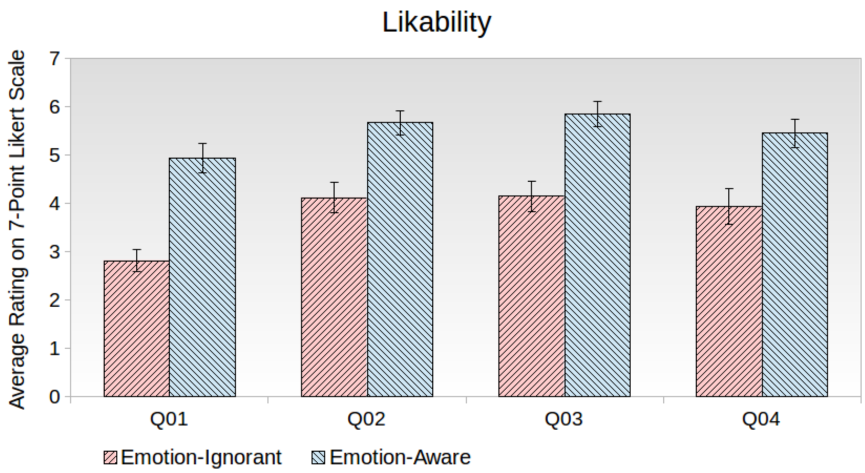

Figure 6.13: Results of the Likert scale surveys for 31 questions. The p-value for the difference between the means for each question is ¡0.001, except for Q????, which is 0.008.

of the experiment.

6.6.1 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 participant. The 31 questions are generally categorized to evaluate the humans' perceptions of the following seven categories, with 3-6 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. Of the 31 questions, 2 were chosen from each group, for a total of 14 questions, for presentation in this paper. The remaining questions were omitted due to space constraints.

The questions presented are provided in Figure **??**. These questions are chosen as representative of their respective groups of questions, and their results do not necessarily represent the highest levels of statistical significance.

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 Figure **??** for the results. As mentioned in Section 6.5.4, 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 and 2 addressed the likability of the robot. As shown in Figure **??**, participants would like to continue working with the emotion-aware robot significantly more than the emotion-ignorant robot by an average of about 1.5 points; additionally participants felt more close to the emotion-aware robot than the emotion-ignorant robot by about 2.1 points, on the 7-point scale. This supports 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 3 and 4 were designed to measure the degree of trust that the human participants felt in the robot. As shown in Figure **??**, participants trusted the emotion-aware robot an average of 1.5 points more than the emotion-ignorant robot, both in general and in terms of collaboration performance. In fact, in Question 4, 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 that the participants felt that the emotion-aware robot's collaborative performance was acceptable. This result supports Hypothesis

2, that posits that human participants would find the emotion-aware robot to be more trustworthy than the emotion-ignorant robot.

Perception of the Robot's Performance

Question 5 (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 6.6.2. The participants also 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

For Questions 7 and 8, participants ranked the emotion-aware robot's understanding of emotions 2.2 and 1.8 points higher, respectively, than the emotion-ignorant robot's understanding of emotions, supporting Hypothesis 4. This category showed the highest total difference between the emotion-ignorant and the emotion-aware robot.

Robot's Understanding of Human and Collaboration Goals

Question 9 was a measure of whether the human perceived that the robot cared about 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 10 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.

Human's Feeling about the Collaboration

Questions 11 and 12 were designed to gauge how the human participants felt about the partnership within the collaboration and the outcome of the collaboration. In the emotion-aware condition, participants scored Questions 11 and 12 as 6.1 and 6.3, respectively, indicating a strong sense of pursuing mutually agreed-upon goals and very high satisfaction with the overall collaboration. It is worth noting that the participants scored Question 11 for the emotion-ignorant case at 5.3 points, leading to a 0.8-point difference between the two conditions; this is the smallest gap that occurs between the results for any question, and indicates that the participants felt that the goals were still partially mutually agreed-upon in the emotion-ignorant case. However, the general satisfaction with the outcome of the collaboration was significantly less in the case of the emotion-ignorant robot, at 4.8 points. These results support Hypothesis 6 that humans will feel greater 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 13 and 14 were designed to measure the human's perception of the robot's satisfaction with the human, and the human's satisfaction with the robot, respectively. The participants provided an average response in the emotion-aware condition of 5.8 and 5.9 to Questions 13 and 14, respectively, indicating a high level of mutual satisfaction; both answers were about 1.5 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.

6.6.2 Results from the Open-Ended Questionnaire

As described in Section 6.5.2, each participant answered an open-ended questionnaire at the end of the study. Figure 6.15 summarizes the questionnaire and which run users preferred for certain conditions (i.e. emotion-ignorant or emotion-aware). Note that some users either chose not to state a preference, or provided ambiguous answers regarding which run they preferred for certain conditions; these results were removed from the analysis. As shown in Figure 6.15, 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, 93.75% 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 40% 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 60% 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, 83.9% 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, 82.8% 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.

6.6.3 Impact of Demographics

As mentioned in Section 6.5.4, 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 consistent pattern emerged. For each of the fourteen questions presented, the younger age group reported higher scores for the emotion-aware robot (except Question 5, which is a reverse-score question). In the emotion-ignorant case, the younger group still scores the robot higher than the older group for 9 questions; for the other 5 questions, the older group scores the emotion-ignorant robot higher. In fact, a pattern emerged in which the score drop between the emotion-aware and the emotion-ignorant case was more for the younger group than for the older group; only questions 4, 6 and 12 broke this pattern.

6.7 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, see Sections 6.6.1 and 6.6.1 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 6.6.1, 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 Sections 6.6.1 and 6.6.1, respectively. 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."

6.8 Conclusions

The goal of our user-study was to compare different aspects of humans' preferences during collaboration with a robot. Our results conclusively showed that humans prefer collaborating with an emotion-aware robot which is capable of a) expressing appropriate emotions, and b) changing collaborative behaviors based on the perceived negative emotions of the human. We are interested to carry out further studies with more capabilities from our framework in order to study collaboration with more complex tasks and evaluate collaborative performance based on objective measures such as cost or time to achieve a shared goal. We believe that emotion-aware robots will outperform emotion-ignorant robots in collaboration with humans.

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

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	« 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	« 0.001
What was the most interesting behavior of the robot and in which run did it happen?	5	24	0.002

Figure 6.15: 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.)

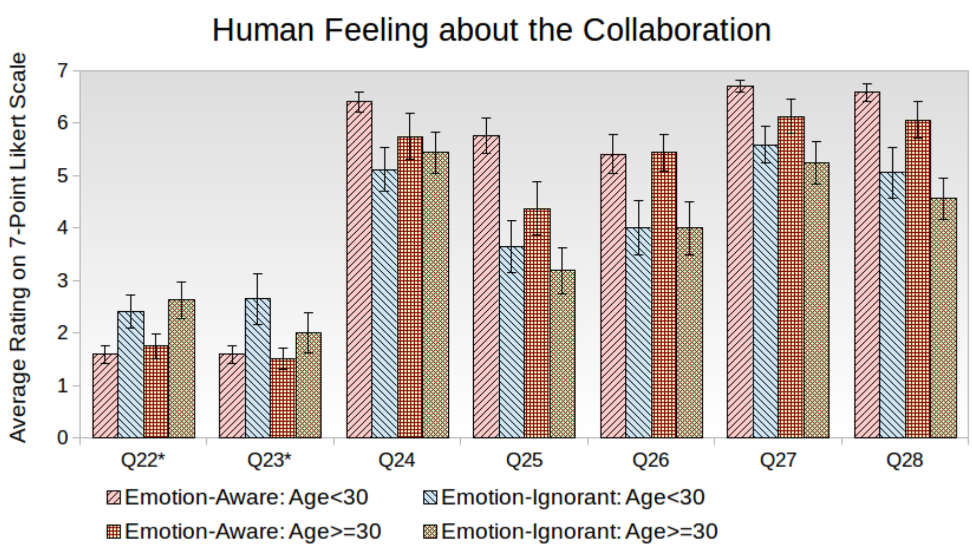

Figure 6.16: Impact of age on results of Likert scale questions related to human's feeling about collaboration.

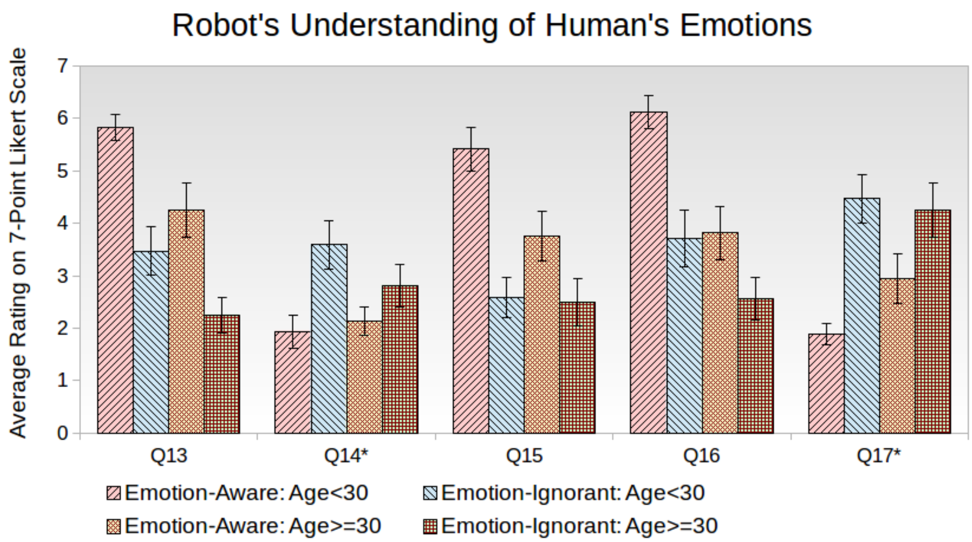

Figure 6.17: Impact of age on results of Likert scale questions related to robot's understanding of human's emotinos.

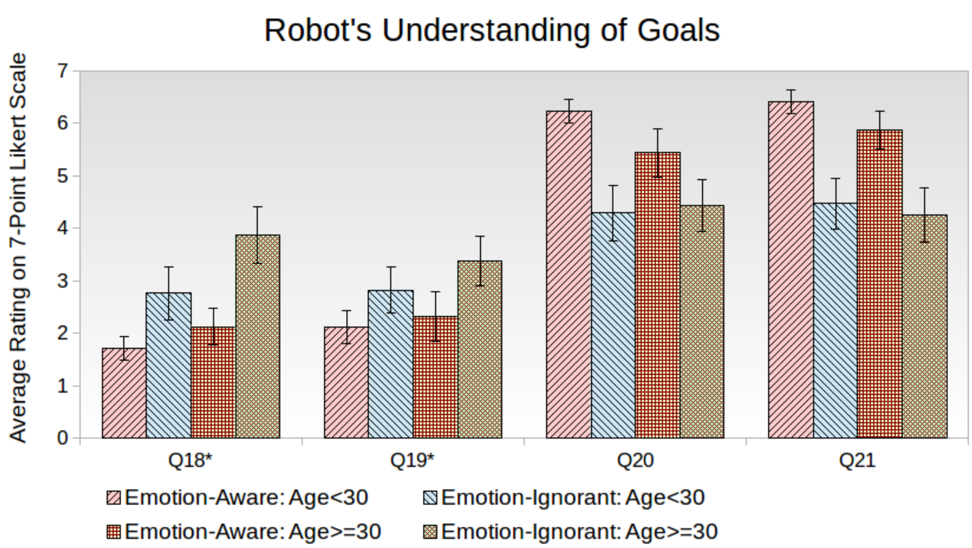

Figure 6.18: Impact of age on results of Likert scale questions related to robot's understanding of goals.

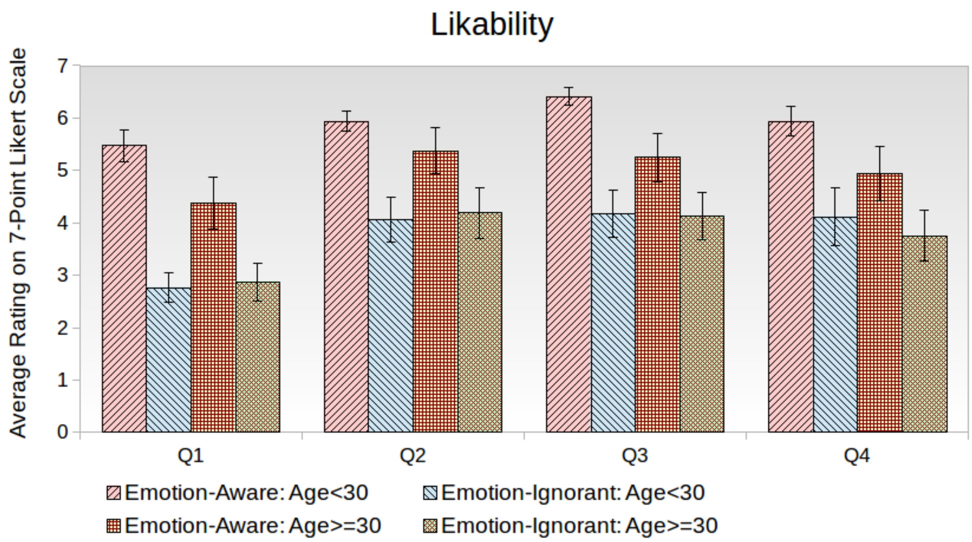

Figure 6.19: Impact of age on results of Likert scale questions related to likability.

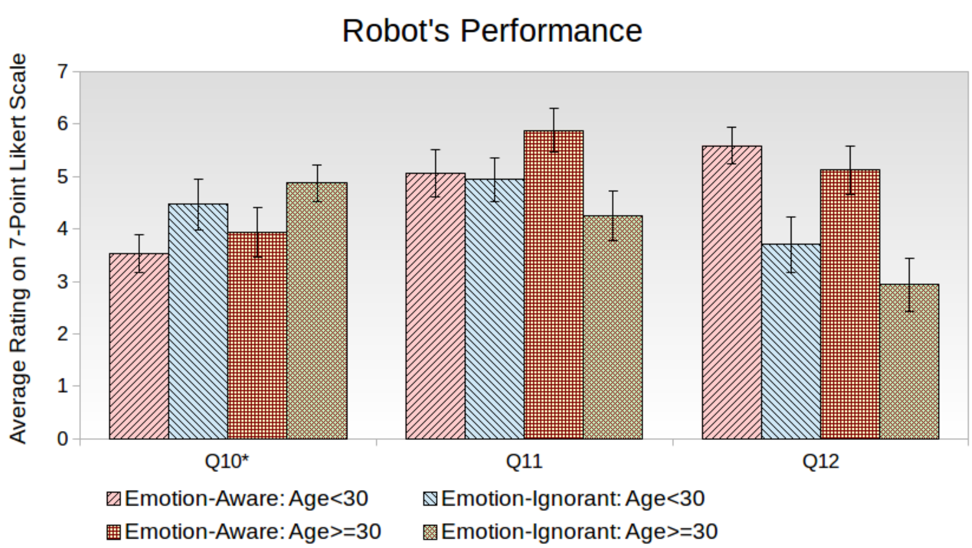

Figure 6.20: Impact of age on results of Likert scale questions related to performance.

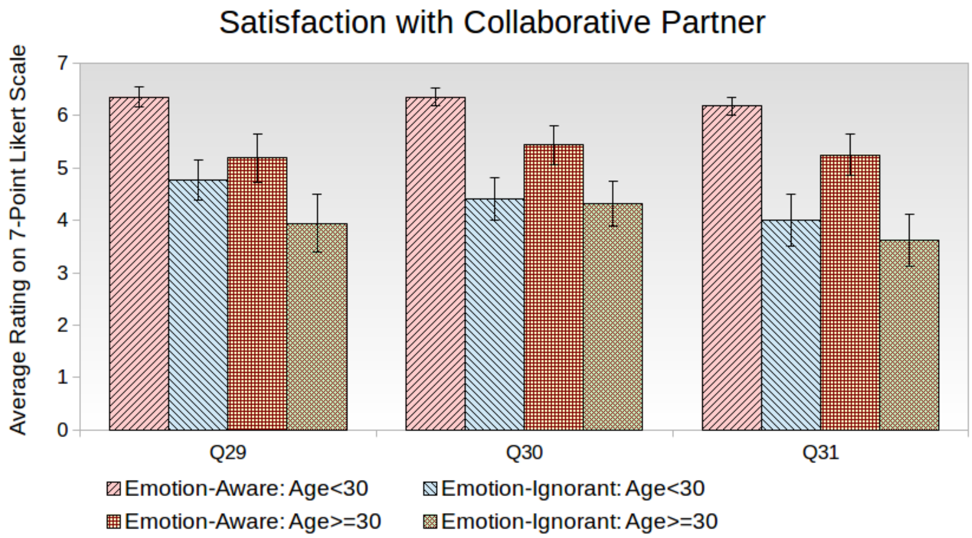

Figure 6.21: Impact of age on results of Likert scale questions related to satisfaction with collaborative partner.

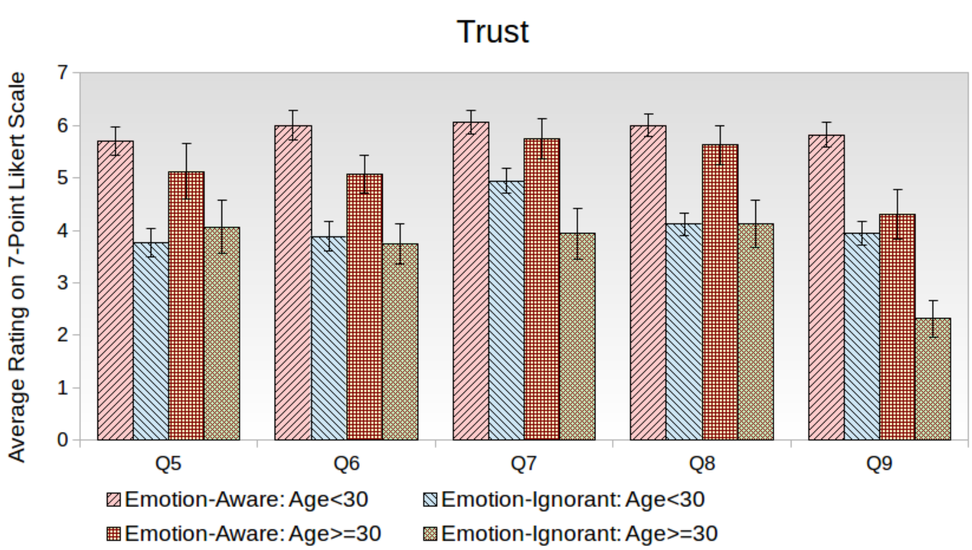

Figure 6.22: Impact of age on results of Likert scale questions related to trust.

CHAPTER 7
CONCLUSION

7.1 Discussion

7.2 Future Work

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APPENDIX A