Toward an Argumentation-based Dialogue framework for Human-Robot Collaboration

Mohammad Quamrul Azhar
Graduate Center, City University of New York

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Toward an Argumentation-based Dialogue Framework for Human-Robot Collaboration

by

Mohammad Q. Azhar

A dissertation submitted to the Graduate Faculty in Computer Science in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2015
This manuscript has been read and accepted by the Graduate Faculty in Computer Science in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

Professor Elizabeth Sklar

__________________________
Date Chair of Examining Committee

Professor Robert Haralick

__________________________
Date Executive Officer

Professor Elizabeth Sklar, Chair
Professor Susan Imberman
Professor Matthew Huenerfauth
Professor Peter McBurney, (Outside Member)

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

iii
Abstract

TOWARD AN ARGUMENTATION-BASED DIALOGUE FRAMEWORK FOR HUMAN-ROBOT COLLABORATION

by

MOHAMMAD Q. AZHAR

Adviser: Professor Elizabeth Sklar

Successful human-robot collaboration with a common goal requires peer interaction in which humans and robots cooperate and complement each other’s expertise. Formal human-robot dialogue in which there is peer interaction is still in its infancy, though. My research recognizes three aspects of human-robot collaboration that call for dialogue: responding to discovery, pre-empting failure, and recovering from failure. In these scenarios the partners need the ability to challenge, persuade, exchange and expand beliefs about a joint action in order to collaborate through dialogue.

My research identifies three argumentation-based dialogues: a persuasion dialogue to resolve disagreement, an information-seeking dialogue to expand individual knowledge, and an inquiry dialogue to share knowledge. A theoretical logic-based framework, a formalized dialogue protocol based on argumentation theory, and argumentation-based dialogue games were developed to provide dialogue support for peer interaction. The work presented in this thesis is the first to apply argumentation theory and three different logic-based argumentation dialogues for use in human-robot collaboration. The research presented in this thesis demonstrates a practical, real-time implementation in which persuasion, inquiry, and information-seeking dialogues are applied to shared decision making for human-robot collaboration in a treasure hunt game domain. My research investigates if adding peer interaction enabled through argumentation-based dialogue to an HRI system improves system performance and user experience during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue. Results
from user studies in physical and simulated human-robot collaborative environments, which involved 108 human participants who interacted with a robot as peer and supervisor, are presented in this thesis. My research contributes to both the human-robot interaction (HRI) and the argumentation communities. First, it brings into HRI a structured method for a robot to maintain its beliefs, to reason using those beliefs, and to interact with a human as a peer via argumentation-based dialogues. The structured method allows the human-robot collaborators to share beliefs, respond to discovery, expand beliefs to recover from failure, challenge beliefs, or resolve conflicts by persuasion. It allows a robot to challenge a human or a human to challenge a robot to prevent human or robot errors. Third, my research provides a comprehensive subjective and objective analysis of the effectiveness of an HRI System with peer interaction that is enabled through argumentation-based dialogue. I compare this peer interaction to a system that is capable of only supervisory interaction with minimal dialogue. My research contributes to the harder questions for human-robot collaboration: what kind of human-robot dialogue support can enhance peer-interaction? How can we develop models to formalize those features? How can we ensure that those features really help, and how do they help?

Human-robot dialogue that can aid shared decision making, support the expansion of individual or shared knowledge, and resolve disagreements between collaborative human-robot teams will be much sought after as human society transitions from a world of robot-as-a-tool to robot-as-a-partner. My research presents a version of peer interaction enabled through argumentation-based dialogue that allows humans and robots to work together as partners.
Acknowledgments

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Contents

1 Introduction 1
  1.1 Research Questions .................................................. 5
  1.2 Research Contribution ............................................... 5
  1.3 Published Work ......................................................... 6
  1.4 Thesis Outline .......................................................... 8

2 Literature Review 10
  2.1 Models of Human-Robot Interaction ................................. 12
  2.2 Human-Robot Dialogue ............................................... 18
    2.2.1 Human-Robot Dialogue Delivery: How to say it ............ 18
    2.2.2 Human-Robot Dialogue Timing: When to say it .......... 21
    2.2.3 Human-Robot Dialogue Content: What to say ............ 22
  2.3 Models of Collaboration ............................................. 27

3 Background 31
  3.1 Argumentation Theory ................................................ 31
3.2 Argumentation-based Dialogue Theory .................................. 34
3.3 Applications of Argumentation-based Dialogues .................. 36

4 Approaches and Methodology .............................................. 38
4.1 The ArgHRI framework ...................................................... 39
  4.1.1 Ontology ............................................................... 39
  4.1.2 Memory system ......................................................... 40
  4.1.3 Argumentation engine ............................................... 41
  4.1.4 Dialogue system ...................................................... 41
4.2 Approach: Argumentation-based Dialogue Games .................. 42
  4.2.1 Dialogue Protocols ................................................... 47
  4.2.2 Axiomatic Semantics ............................................... 58
  4.2.3 Control Layer ......................................................... 60
4.3 Experimental Domain: The Treasure Hunt Game .................... 66
  4.3.1 Map ................................................................. 68
  4.3.2 Treasures ............................................................ 68
  4.3.3 Tasks ................................................................. 69
  4.3.4 Dependencies ......................................................... 70
  4.3.5 Robots ............................................................ 70
  4.3.6 Score ................................................................. 70
4.4 Experimental Methodology ............................................... 71
  4.4.1 Full-Dialogue Mode ................................................. 73
  4.4.2 Minimal-Dialogue Mode ........................................... 79

5 ArgHRI System: A Live HRI System ................................. 81
5.1 System Design ........................................................... 81
5.2 System Architecture ..................................................... 83
5.2.1 ArgHRI Core System .................................................. 84
5.2.2 Integration of ArgHRI and ArgTrust .............................. 88
5.2.3 Integration of ArgHRI and HRTeam ............................. 90
5.2.4 Experimental Modules .............................................. 91
5.3 Human-Robot Interface ................................................. 93
  5.3.1 Enhancing Situational Awareness ............................... 94
  5.3.2 Lowering Cognitive Load .......................................... 96
  5.3.3 Reducing Human Errors ........................................... 96
  5.3.4 Human Decision Making .......................................... 97
  5.3.5 Critique of User Interface ........................................ 106
5.4 Software Development ................................................ 109

6 Preliminary User Studies .................................................. 112
  6.1 Pilot Study .............................................................. 114
     6.1.1 Pilot Study A: ................................................... 114
     6.1.2 Pilot Study B: ................................................... 116
     6.1.3 Data Collection and Analysis: ................................. 118
  6.2 User Study 1 ........................................................... 120
     6.2.1 Experimental Procedure: .................................... 121
     6.2.2 Data Collection and Analysis: ................................. 122
  6.3 Discussion .............................................................. 124

7 Final User Study Results ................................................... 130
  7.1 Experimental Protocol: .............................................. 131
  7.2 Data Collection: ...................................................... 132
  7.3 User Study 2 Analysis ................................................ 134
     7.3.1 Participants: .................................................... 134
7.3.2 Objective Analysis: ......................................................... 135
7.3.3 Subjective Analysis: ....................................................... 141
7.4 Full-Dialogue Analysis: ..................................................... 146

8 Conclusion ................................................................. 157
8.1 Research Contribution ................................................... 157
8.2 Future Work ............................................................... 161

Appendices ................................................................. 165
A ArgTrust and HRTeam ..................................................... 166
A.1 HRTeam Commands and Data Collection ................. 166
A.2 XML for ArgTrust ......................................................... 168
A.2.1 input XML for ArgTrust ........................................... 168
A.2.2 Output XML file from ArgTrust ......................... 171

B Final User Study Survey Questionnaire ......................... 176

C A Live ArgHRI System Demonstration ......................... 192
C.1 Experimental Setup Demonstration ......................... 193
C.2 Minimal-Dialogue Mode Demonstration ................. 195
C.3 Full-Dialogue Mode Demonstration ......................... 200

D Final User Study Results ................................................ 214
D.1 Section: Demographic ................................................... 215
D.1.1 Gender ................................................................. 215
D.1.2 Age ................................................................. 215
D.1.3 Level in School ....................................................... 216
D.1.4 Level of Education .................................................. 216
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>D.1.5</td>
<td>Computer Usage</td>
<td>217</td>
</tr>
<tr>
<td>D.1.6</td>
<td>Major</td>
<td>218</td>
</tr>
<tr>
<td>D.1.7</td>
<td>Robot Experience</td>
<td>220</td>
</tr>
<tr>
<td>D.1.8</td>
<td>Robot Experience</td>
<td>220</td>
</tr>
<tr>
<td>D.2</td>
<td>Section I: Agent/Robot Level View</td>
<td>221</td>
</tr>
<tr>
<td>D.2.1</td>
<td>COLLABORATION</td>
<td>221</td>
</tr>
<tr>
<td>D.2.2</td>
<td>TRUST</td>
<td>222</td>
</tr>
<tr>
<td>D.2.3</td>
<td>COMMUNICATION</td>
<td>224</td>
</tr>
<tr>
<td>D.2.4</td>
<td>TASK SUCCESS/PERFORMANCE</td>
<td>225</td>
</tr>
<tr>
<td>D.2.5</td>
<td>USERS VIEW OF COLLABORATION</td>
<td>226</td>
</tr>
<tr>
<td>D.3</td>
<td>Section II: System/Task Level View</td>
<td>228</td>
</tr>
<tr>
<td>D.3.1</td>
<td>ROBOT EFFORT</td>
<td>228</td>
</tr>
<tr>
<td>D.3.2</td>
<td>ROBOT-RELIABILITY-TASK-SUCCESS</td>
<td>229</td>
</tr>
<tr>
<td>D.3.3</td>
<td>TASK-COMPLETION</td>
<td>231</td>
</tr>
<tr>
<td>D.3.4</td>
<td>FULL DIALOGUE/SYSTEM EFFECT</td>
<td>232</td>
</tr>
<tr>
<td>D.3.5</td>
<td>FULL DIALOGUE/SYSTEM EFFECT</td>
<td>233</td>
</tr>
<tr>
<td>D.4</td>
<td>Section III</td>
<td>235</td>
</tr>
<tr>
<td>D.5</td>
<td>HRTeam Data Analysis</td>
<td>240</td>
</tr>
<tr>
<td>D.5.1</td>
<td>Trajectory Logs</td>
<td>241</td>
</tr>
<tr>
<td>D.6</td>
<td>Dialogue Analysis</td>
<td>249</td>
</tr>
</tbody>
</table>

**Bibliography** 252
# List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Example domains, users and tasks found in HRI literature revised from Sklar and Azhar, 2015.</td>
<td>3</td>
</tr>
<tr>
<td>4.1</td>
<td>Our notation: types of knowledge, or partitions, of agent’s belief set</td>
<td>44</td>
</tr>
<tr>
<td>4.2</td>
<td>Pre-conditions: robot’s views about $b$ prior to dialogue.</td>
<td>45</td>
</tr>
<tr>
<td>4.3</td>
<td>Cases for different types of dialogues.</td>
<td>45</td>
</tr>
<tr>
<td>4.4</td>
<td>Pre-conditions: persuasion dialogue.</td>
<td>49</td>
</tr>
<tr>
<td>4.5</td>
<td>$assert(b)$ locution and possible moves during persuasion dialogue.</td>
<td>49</td>
</tr>
<tr>
<td>4.6</td>
<td>Pre-conditions: inquiry dialogue.</td>
<td>51</td>
</tr>
<tr>
<td>4.7</td>
<td>$propose(a \rightarrow b)$ locution and possible moves during inquiry dialogue.</td>
<td>52</td>
</tr>
<tr>
<td>4.8</td>
<td>Pre-conditions: information-seeking dialogue.</td>
<td>54</td>
</tr>
<tr>
<td>4.9</td>
<td>$question(b)$ locution and possible moves during information-seeking dialogue.</td>
<td>55</td>
</tr>
<tr>
<td>4.10</td>
<td>Opening moves.</td>
<td>60</td>
</tr>
<tr>
<td>4.11</td>
<td>Possible <strong>pre-conditions</strong> and corresponding Argumentation-based Dialogues for discussing <strong>where to search</strong>.</td>
<td>75</td>
</tr>
<tr>
<td>4.12</td>
<td>Possible <strong>pre-conditions</strong> and corresponding Argumentation-based Dialogues for discussing <strong>how to get there</strong>.</td>
<td>77</td>
</tr>
</tbody>
</table>
4.13 Possible **pre-conditions** and corresponding Argumentation-based Dialogues for discussing the **identity of the treasure** ........................................ 79

5.1 The Processing steps of our modified robot control structure [Sklar and Azhar, 2015]. .......................................................... 88

5.2 Evaluation of ArgHRI Interface following USAR Guidelines ...................... 108

6.1 A Summary of all User Studies with 108 human participants ....................... 112

6.2 Average survey results across 6 participants from pilot study [Azhar et al., 2013b]. 120

6.3 Average survey results across 20 participants from **simulation experiments using virtual robot from User Study 1**. .......................... 123

6.4 Average survey results across 19 participants from **live experiments using physical robot from User Study 1**. ................................. 124

7.1 User Study 2 Experimental Procedures ............................................ 132

7.2 Summary of Hypotheses Results based on a statistical analysis of Repeated t-tests from Physical Experiments (number of participants=27) on Performance Metrics. 140

7.3 Summary of Hypotheses Results based on a statistical analysis of Repeated t-tests from Simulation Experiments (number of participants=33) on Performance Metrics. 140

7.4 In-experiment Survey Questions. .................................................. 143

7.5 Summary of Hypotheses Results from Subjective Analysis of Physical Experiments (number of human participants=27). .......................... 144

7.6 Summary of Hypotheses Results from Subjective Analysis of Simulation Experiments (number of human participants=33). .......................... 145

7.7 Argumentation-based Dialogues triggered during **where to search** discussion .......................... 148
7.8 Argumentation-based Dialogues triggered during **where to search** discussion where
Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona,
Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with
disagreement ................................................................. 148

7.9 Argumentation-based Dialogues triggered during **how to get there** discussion . . . 149

7.10 Argumentation-based Dialogues triggered during **how to get there** discussion where
Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona,
Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with
disagreement ................................................................. 149

7.11 Argumentation-based Dialogues triggered during **what is found there** discussion
where Ch= ArgHRI Dialogue was challenged either by human collaborator or
robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue
ends with disagreement .................................................... 150

B.1 User Study 2 Experimental Procedures ............................................. 177

C.1 Experimental Setups for User12 from Final User Study ......................... 194

C.2 A Reenacted sample Game Master Messages from Game 2 played by the human
subject User12 and Robot Mary in **minimal-dialogue** mode ..................... 196

C.3 Results from Game1 played by the human subject User12 and Robot Fiona in **full-
dialogue** mode ................................................................. 212

D.1 ArgDialogue Categories Explained ..................................................... 214

D.2 Robot Trajectory Logs from Physical Experiment (User 1-User 10). D1=Full Di-
alogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary;
D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with
Robot Mary ................................................................. 242
D.3 Robot Trajectory Logs from Physical Experiment (User 11-User 20). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary .......................................................... 243

D.4 Robot Trajectory Logs from Physical Experiment (User 21-User 30). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary .......................................................... 244

D.5 Robot Trajectory Logs from Simulation Experiment (User 1-User 10). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary .......................................................... 245

D.6 Robot Trajectory Logs from Simulation Experiment (User 11-User 20). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary .......................................................... 246

D.7 Robot Trajectory Logs from Simulation Experiment (User 11-User 20). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary .......................................................... 247

D.8 Robot Trajectory Logs from Simulation Experiment (User 31-User 33). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary .......................................................... 248

D.9 Argumentation-based Dialogues triggered during where to go discussion ........ 249
D.10 Argumentation-based Dialogues triggered during **where to go** discussion where
Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona,
Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with
disagreement .................................................... 249

D.11 Argumentation-based Dialogues triggered during **how to get there** discussion . . 249

D.12 Argumentation-based Dialogues triggered during **how to get there** discussion where
Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona,
Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with
disagreement .................................................... 250

D.13 Argumentation-based Dialogues triggered during **what is found there** discussion
where Ch= ArgHRI Dialogue was challenged either by human collaborator or
robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue
ends with disagreement .................................... 250

D.14 Argumentation-based Persuasion Dialogues (R2H) triggered during **where to go**
discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI
Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement . . 250

D.15 Argumentation-based InfoSeek Dialogues (H2R) triggered during **where to go** dis-
cussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI
Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement . . 250

D.16 Argumentation-based Persuasion Dialogues (R2H) triggered during **how to get there**
discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI
Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement . . 250

D.17 Argumentation-based InfoSeek Dialogues (H2R) triggered during **how to get there?**
discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI
Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement . . 251
## List of Figures

2.1 The possible combinations of single or multiple humans (H) and robots (R), acting as individuals or in teams. (from [Yanco and Drury, 2002])  
2.2 Human-robot interactions must be considered from multiple perspectives (from Ferketic et al. [2006])  
3.1 Forms of **attack** between arguments: \( c_1 \) rebuts \( c_2 \), and, symmetrically, \( c_2 \) rebuts \( c_1 \); \( c_1 \) undermines \( S_2 \); and \( c_2 \) undermines \( S_1 \) [Sklar and Azhar, 2015].  
3.2 An example of **rebuttal**  
3.3 Forms of **support** between arguments: \( c_1 \in S_2 \) and thus p-supports \( c_2 \); \( c_2 \in S_1 \) and thus p-supports \( c_1 \); \( S_1' \) c-supports \( c_1 \), where \( S_1 \cap S_1' = \emptyset \) [Sklar and Azhar, 2015].  
4.1 Persuasion Dialogue protocol, drawn as a state machine. The start state is indicated with an \( \circ \). Termination states are indicated with double circles. States shown without fill are states in which the initiating agent is expected to make a move in the dialogue game; states filled in grey are states in which the responding agent is expected to make a move [Sklar and Azhar, 2015].
4.2 Inquiry Dialogue protocols, drawn as a state machine. The start state is indicated with an $s$. Termination states are indicated with double circles. States shown without fill are states in which the initiating agent is expected to make a move in the dialogue game; states filled in grey are states in which the responding agent is expected to make a move [Sklar and Azhar, 2015].

4.3 Information-Seeking Dialogue protocol, drawn as a state machine. The start state is indicated with an $s$. Termination states are indicated with double circles. States shown without fill are states in which the initiating agent is expected to make a move in the dialogue game; states filled in grey are states in which the responding agent is expected to make a move [Sklar and Azhar, 2015].

4.4 Example 1

4.5 Example 2

4.6 Axiomatic Semantics.

4.7 Control layers for different combinations of dialogues. A diamond-shaped node labeled $CL$ represents the control layer. A round node labeled $d.sl$ represents the beginning state of a dialogue, and $d.f$ represents the end state of the dialogue. The $*$ between the $d.sl$ and $d.f$ nodes indicate a variable number of internal states for each dialogue. When multiple dialogues occur concurrently, as in (b) and (c), the states of the different dialogues are distinguished by the prefixes $d1$ and $d2$, instead of $d$.

4.8 Opportunities for Full Dialogue in a Treasure Hunt Game.

5.1 ArgHRI System Architecture

5.2 ArgHRI Graphical User Interface

5.3 Argumentation-based dialogues and corresponding dialogue moves during “where to search” discussion

5.4 Robot control architecture, with dialogue step added. [Sklar and Azhar, 2015]
6.5 Box-and-whiskers plots of results from User Study 1. Thick red horizontal bars indicate the median. Boxes extend from 25th percentile to 75th percentile. Whiskers extend from minimum value to maximum. Y-axis values correspond to Likert-scale answers provided by participants in user study, ranging from 1 = strongly disagree to 5 = strongly agree. Blue boxes correspond to simulated robot experimental condition (20 participants), and green boxes correspond to live robot experimental condition (19 participants).

6.6 Statistical plots of results from User Study 1. Thick magenta horizontal bars indicate the mean. Boxes extend from 2 standard deviations below the mean to 2 standard deviations above the mean. Y-axis values correspond to Likert-scale answers provided by participants in user study, ranging from 1 = strongly disagree to 5 = strongly agree. Blue boxes correspond to simulated robot experimental condition (20 participants), and green boxes correspond to live robot experimental condition (19 participants).

7.1 Physical Experiment (n = 27): Total Distance Traveled

7.2 Physical Experiment (n = 27): Total Execution Time

7.3 Simulation Experiment (n = 33): Total Distance Traveled

7.4 Simulation Experiment (n = 33): Total Execution Time

C.1 ArgHRI System and Treasure Hunt Game Map

C.2 Extracted GUI log for experimental setup from Game1 played by User12 and Robot Fiona in full-dialogue mode

C.3 Extracted GUI log for experimental setup from Game2 played by User12 and Robot Mary in minimal-dialogue mode

C.4 The Reenacted Game2 Welcome Window for minimal-dialogue mode with Treasure Set 2 during the physical experiment for User12
C.5 The Reenacted ArgHRI Planning Window from the THG Game 2 played by the
human subject User12 and Robot Mary in minimal-dialogue mode . . . . . . . . . 197
C.6 Extracted Dialogue Logs for Planning from minimal-dialogue panel from THG
Game2 played by the human subject User12 and Robot Mary in minimal-dialogue
mode . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 197
C.7 Extracted GUI log from the minimal-dialogue panel of THG Game2, played by
User12 and Robot Mary in minimal-dialogue mode . . . . . . . . . . . . . . . . . 198
C.8 The Reenacted ArgHRI Treasure Identification Window from THG Game2 played
by User12 and Robot Mary in minimal-dialogue mode . . . . . . . . . . . . . . . 198
C.9 Extracted GUI log from treasure-identification panel from THG Game2 played by
User12 and Robot Mary in minimal-dialogue mode . . . . . . . . . . . . . . . . . 199
C.10 Trajectory Path for Robot Mary (2− > 3− > 6− > 5) from Game 2 played by
User12 in minimal-dialogue mode . . . . . . . . . . . . . . . . . . . . . . . . . . 200
C.11 The Reenacted Game2 Welcome Window for minimal-dialogue mode with Treasure Set 2 during the physical experiment for User12 . . . . . . . . . . . . . . . . 201
C.12 Extracted GUI Logs for the “where to search” discussion from the full-dialogue
panel. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 202
C.13 A Reenacted ArgHRI Interface Scenes for a persuasion dialogue during “where to
search” discussions. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 204
C.14 A Reenacted ArgHRI Interface Scenes for User12’s initial plans. . . . . . . . . . . 205
C.15 Reenacted ArgHRI Interface Scenes for a persuasion dialogue during “how to get
there” discussions. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 208
C.16 Reenacted ArgHRI Interface Treasure Identification Window during “what is found
in Room4” discussion. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 209
C.17 Trajectory Path for Robot Fiona (4− > 5− > 6− > 3) from Game1 played by
User12 in full-dialogue mode . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 213
xxi


D.1 Live Experiment: Total Distance Traveled ........................................ 240
D.2 Live Experiment: Total Execution Time .......................................... 240
D.3 Simulation Experiment: Total Distance Traveled ......................... 241
D.4 Simulation Experiment: Total Execution Time ............................ 241
Chapter 1

Introduction

A successful human-robot team with a common goal needs to support interaction where humans and robots can complement each other’s expertise and seek each other’s help [Groom and Nass, 2007]. For example, a robot in a search and rescue scenario can seek a human’s help identifying human victims. Human-robot dialogue may play a crucial role in human-robot communication.

Over the years, many interactive and collaborative social robots have been deployed in military and police applications [Lin et al., 2008], education (e.g., robot-tutor [Kennedy et al., 2015]), space (e.g., Robonaut [Fong et al., 2006a]), urban search and rescue (USAR), home entertainment (e.g., AIBO [Fujita and Kitano, 1998]), and during natural or man-made disasters (e.g., Search and Rescue Robot [Murphy, 2004]). There are two contrasting models for designing robots that interact with humans in the physical world [Kidd, 2003]. In one model, robots are designed as tools similar to a screwdriver or wrench in that they lack the capacity for input and are incapable of acting without direct human operator inputs. In the other model, robots act as a partner and are designed to accomplish at least low-level tasks (i.e., pick up an object). They rely on human supervisory inputs for high-level decisions (i.e., where to search). The robot that is capable of collaborating as a peer needs to be capable of making high-level decisions by communicating with its human peers about joint action [Hoffman and Breazeal, 2004; Breazeal et al., 2004]. Human-robot dialogue has been used by space robots to make shared-decisions and by assistive robots for
search and rescue missions [Fong et al., 2001, 2003].

As with two humans, human-robot dialogue requires sharing information and taking the initiative. The style of dialogue varies based on task, interaction, and environment. A robot in a subordinate relationship with a human collaborator requires the least amount of human-robot dialogue communication since the human collaborator acts as a **supervisor** [Scholtz, 2003] and takes responsibility for making decisions about joint actions and actions that affect others. In contrast, the robot in a partner relationship with a human collaborator requires efficient human-robot dialogue communication since the human collaborator acts as a **peer** [Scholtz, 2003] and shares responsibility for making decisions about joint actions and actions that affect others.

Thus, a **peer** robot, an embodied agent, is identified in this research as a robot that is capable of working with a human as a partner to provide or seek help from a human collaborator. As in human-human collaboration, an ideal peer interaction requires that both robot and human expand their knowledge by seeking information from each other when one partner does not know something but assumes that the other partner does. In those cases, both partners have incomplete information. They need to engage in an inquiry to find complete information. Both collaborating partners need to persuade each other when they have conflicting beliefs. Most important, both partners should be able to defend or justify individual beliefs, if challenged. Human-robot dialogue support for peer interaction in which a human and robot work together is still in its infancy [Mutlu et al., 2015]. Argumentation-based dialogues can provide human-robot dialogue support for such peer interaction. This research identified three different argumentation-based dialogues that can provide human-robot dialogue support: **information-seeking dialogues** to share knowledge, **inquiry dialogues** to expand knowledge, and **persuasion dialogues** to resolve conflicting beliefs that otherwise can lead to human or robot errors. In this thesis, these three argumentation-based dialogues, referred to as **full dialogue**, support peer interaction. **Minimal dialogue**, which refers to a lack of full-dialogue, supports supervisory interaction in which a robot solely listens and obeys commands from humans. In the remainder of this thesis, minimal-dialogue mode refers to a scripted
dialogue interaction where a robot obeys a human participant’s commands as a subordinate, and full-dialogue mode refers to dialogues that allows a human and robot to expand knowledge by inquiry, share knowledge via information-seeking, or challenge or persuade each other as peers. The research in this thesis measures the impact of human-robot dialogue and compares the impact of full dialogue in peer interaction and minimal dialogue in supervisory interaction involving a one-human and one-robot team.

<table>
<thead>
<tr>
<th>domain</th>
<th>human user</th>
<th>robot tasks</th>
</tr>
</thead>
<tbody>
<tr>
<td>search and rescue</td>
<td>first responder</td>
<td>search for victims; communicate with victims; find safe path to victim for first responders</td>
</tr>
<tr>
<td>[Murphy et al., 2001]</td>
<td></td>
<td></td>
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<tr>
<td>[Murphy, 2004]</td>
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</tr>
<tr>
<td>[Yanco et al., 2006]</td>
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<tr>
<td>humanitarian de-mining</td>
<td>NGO worker</td>
<td>find mines; find safe path to mine for demining specialist</td>
</tr>
<tr>
<td>[Santana et al., 2007]</td>
<td></td>
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<tr>
<td>[Habib, 2007]</td>
<td></td>
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</tr>
<tr>
<td>manufacturing</td>
<td>factory worker</td>
<td>product assembly</td>
</tr>
<tr>
<td>[Alers et al., 2014]</td>
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<tr>
<td>health aid</td>
<td>patient</td>
<td>administer medication; assist with physical therapy</td>
</tr>
<tr>
<td>[Matthews, 2002]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>geriatric companion</td>
<td>elderly person</td>
<td>administer medication; observe behavior; engage in exercise; read out loud; answer telephone/door</td>
</tr>
<tr>
<td>[Wada et al., 2002]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>tutor</td>
<td>student</td>
<td>play educational games; encourage learning activities</td>
</tr>
<tr>
<td>[Castellano et al., 2013]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>space robot</td>
<td>astronaut</td>
<td>space exploratory tasks; hangar construction, habitat inspection, and in-situ resource collection and transport</td>
</tr>
<tr>
<td>[Fong et al., 2006a]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1.1: Example domains, users and tasks found in HRI literature revised from [Sklar and Azhar, 2015].

Unlike human-human dialogue, current human-robot dialogue support does not offer the opportunity for humans and robots to expand, exchange, or challenge ideas, nor does it allow for them to use ideas to persuade or to resolve conflicts during human-robot collaboration. It does not
allow for discussions of options about shared decision making via structured conversation.

This research identifies three specific cases within the domains and situations generally explored in the HRI literature, where the ability to challenge, persuade, exchange and expand beliefs about a joint action as discussed through dialogue can enable peer collaboration. They are documented in [Sklar and Azhar, 2015]: (1) responding to discovery, (2) pre-empting failure, and (3) recovering from failure. Table 1.1 lists detailed example of domains, tasks and users commonly found in the HRI literature.

The research presented in this thesis applied argumentation theory [Rahwan and Simari, 2009], argumentation-based dialogue games, and associated rules [Walton and Krabbe, 1995; Hulstijn, 2000; McBurney and Parsons, 2002; Prakken, 2006] identities four different real world human-robot collaborative scenarios for three types-of human-robot dialogues that are extended from argumentation-based dialogue:

- a human can persuade a robot to prevent robot errors by employing persuasion dialogue [Prakken, 2006] in which a human agent tries to alter the beliefs of a robot agent.
- a robot can ask a human for information that the robot does not have but believes that the human has and vice versa by employing information-seeking dialogue [Walton and Krabbe, 1995] in which an agent asks a question to which it believes the other agent knows the answer.
- a robot discovers information that a human does not know or that contradicts something the human knows. In this case, a robot agent tries to alter the beliefs of a human agent by employing persuasion dialogue [Prakken, 2006].
- a robot and human together agree to find an answer to something neither of them knows by employing inquiry dialogue [McBurney and Parsons, 2001] in which two agents collaboratively seek the answer to a question to which neither knows the answer.
1.1 Research Questions

The overall goal of this thesis is motivated by the following research questions:

1. *Does adding peer interaction enabled through argumentation-based dialogue to an HRI system improve system performance during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?*

2. *Does adding peer interaction enabled through argumentation-based dialogue to an HRI system improve user experience during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?*

1.2 Research Contribution

My research contributes to both the human-robot interaction (HRI) and the argumentation communities: first, by bringing into HRI a structured method for a robot to maintain its beliefs, to reason using those beliefs, and to interact with a human via dialogue to share beliefs, expand beliefs, challenge beliefs, or resolve conflicts by persuasion; second, by demonstrating a practical, real-time implementation in which three types of argumentation-based dialogues are successfully applied; and third, by comprehensive subjective and objective analysis of the effectiveness of argumentation-based dialogue in full-dialogue mode when compared to a user study that employs minimal-dialogue mode. My research will contribute:

- A logic-based framework for human-robot interaction that generates dialogues and provides support for dialogue that can resolve conflicting beliefs during human-robot collaboration.

- A dialogue framework that provides tools to resolve conflicts during human-robot collaboration in a search and rescue domain that employs persuasion dialogue.
• A dialogue framework for human-robot interaction that provides support for error diagnosis during human-robot collaboration by providing dialogue support in a search and rescue domain that employs information-seeking and inquiry dialogue.

• A dialogue framework that is integrated into the planning and the decision making of a human-robot collaborative task. Each dialogue locution uttered by the robot is supported by arguments. If asked or challenged, the robot will be able to provide evidence to support its reasoning during collaboration.

• A subjective and objective analysis of the effectiveness of a full dialogue that employs argumentation-based dialogue when compared to a user study employing minimal-dialogue mode in the search and rescue domain.

My research also contributes to the argumentation community. The work presented in this thesis is the first to apply argumentation theory and three different logic-based argumentation-dialogues for human-robot collaboration to share, challenge, and expand knowledge and persuade each other to resolve conflicts so that beliefs in a collaborative task can be aligned.

1.3 Published Work

The research presented in this thesis has been developed under the supervision of my mentor Professor Elizabeth Sklar and committee members, Professor Susan Imberman, Professor Matthew Huenerfauth, and Professor Peter McBurney. Parts of the thesis work with Professor Sklar have been previously published:

• Chapter 1 introduces two research questions investigated in this thesis that employ argumentation-based dialogue to enhance peer interaction for human-robot collaboration. They were first published in “Toward an argumentation-based dialogue framework for human-robot collaboration” in the Proceedings of the 14th ACM International Conference on Multimodal Inter-
• Part of our argumentation-based dialogue approach and experimental domain for human-robot collaboration detailed in Chapter 3 will be published as “Argumentation-based dialogue games for shared control in human-robot systems” in the *Journal of Human-Robot Interaction*, (forthcoming), 2015, [Sklar and Azhar, 2015].

• Our theoretical argumentation approach for human-robot collaboration was published earlier as “A Case for Argumentation to Enable Human-Robot Collaboration” in the *Proceedings of the Workshop on Argumentation in Multiagent Systems* (ArgMAS) at Autonomous Agents and MultiAgent Systems (AAMAS), St Paul, MN, USA, May 2013b, [Sklar et al., 2013c] and as “A Case for Argumentation to Enable Human-Robot Collaboration” (Extended Abstract) in the *Proceedings of Autonomous Agents and Multiagent Systems* (AAMAS), 2013a, [Sklar et al., 2013a].

• The ArgHRI System 1.0 employed in the Pilot Study that supported only persuasion dialogue was developed as a proof-of-concept prototype of a logic-based dialogue framework grounded in argumentation theory. It addresses the “what to say” problem in human-robot communication during a collaborative task discussed in Chapter 4 and was published as “An Argumentation-based Dialogue System for Human-Robot Collaboration (Demonstration)” in the *Proceedings of Autonomous Agents and Multiagent Systems* (AAMAS), St Paul, MN, USA, May 2013a, [Azhar et al., 2013a].

• Our first implementation and subjective evaluation of the ArgHRI system (1.0) in a treasure hunt experimental search domain, which demonstrated an argumentation-based dialogue model employing persuasion dialogue to support human-robot communication and explore our first hypothesis, discussed in Chapter 5, as the pilot user study and its subjective analysis, was published as “Evaluation of an argumentation-based dialogue system for
human-robot collaboration” in the *Proceedings of the Workshop on Autonomous Robots and Multirobot Systems* (ARMS) at Autonomous Agents and MultiAgent Systems (AAMAS), 2013b, [Azhar et al., 2013b].

### 1.4 Thesis Outline

This thesis is organized as follows.

- **Chapter 1** (i.e., this chapter) provides the motivation and problem domain for my research and details the research questions and contributions for this thesis.

- **Chapter 2** provides a literature review on relevant topics to the research presented in this thesis.

- **Chapter 3** provides a theoretical background to the research presented in this thesis.

- **Chapter 4** describes our argumentation-based dialogue game approach and an argumentation-based dialogue framework for human-robot collaboration. A formal description of our experimental domain and experimental methodology are presented here.

- **Chapter 5** details the design and implementation of a human-robot-system system where a human and robot can share decision making and engage in a dialogue about their joint action in the search and rescue domain as peers applying theoretical argumentation-based dialogue games and the ArgHRI framework enumerated in **Chapter 4**.

- **Chapter 6** gives descriptions and subjective analysis from the results of the preliminary user studies, including pilot study A ($n = 3$), pilot study B ($n = 6$) and a phase 1 user study — ($n = 39$) to investigate if adding *peer interaction enabled through argumentation-based dialogue* to an HRI system improves *user experience* during a collaborative task when compared to an HRI system that is capable of only *supervisory interaction with minimal dialogue*. 
• **Chapter 7** details descriptions and subjective and objective analysis from the results of the final User study II \((n = 60)\) to investigate if adding *peer interaction enabled through argumentation-based dialogue* to an HRI system improves *user experience* during a collaborative task when compared to an HRI system that is capable of only *supervisory interaction with minimal dialogue*.

• **Chapter 8** summarizes the contributions made in this thesis and identifies possible future research directions.
Chapter 2

Literature Review

**Human-Robot Interaction (HRI)** is an emerging field that studies the interactions and relationships between humans and robots. It is a multidisciplinary field that employs active computer science research fields, such as human-computer interaction (HCI), robotics, machine learning, natural language processing, computer vision, cognitive psychology, and design [Adams, 2002; Scholtz, 2003; Goodrich and Schultz, 2007]. In this research, a robot is an *embodied agent* in the dynamic physical environment. Interactive social robots are being deployed in military and police applications, education, space, home, and industry [Fong et al., 2003; Goodrich and Schultz, 2007; Mutlu et al., 2015]. Unlike traditional computers, mobile robots need to interact with and adapt to the dynamic, chaotic, and uncertain nature of their physical environment. The interaction may be as simple as calibrating a robot’s sensor values due to changes in the environment.

Goodrich and Schultz [2007] define Human-Robot Interaction (HRI) as follows:

**Human-Robot Interaction (HRI)** is a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans. Interaction, by definition, requires communication between robots and humans [Goodrich and Schultz, 2007].
Communication is an important requirement for successful human-robot collaboration and a challenging puzzle [Mutlu et al., 2015; Goodfellow et al., 2010; Hoffman and Breazeal, 2004], and dialogue is a communication process between two or more parties [Fong et al., 2003] that has been considered a natural means for humans to communicate with robots.

A range of issues need to be considered, such as the purpose of communication, the medium through which communication is facilitated, and the direction of information flow [Klingspor et al., 1997]. Examining each of these considerations further raises additional questions. What kind of information is exchanged? What is the purpose of the information being exchanged? At what level is the information abstracted? How is the information transferred—orally, via gestures or via some other type of interaction (e.g., text message)? How is the content transferred—natural language or some type of specialized command language? Does information flow from the human to the robot, vice versa, or in both directions?

Due to the dynamic physical nature of this interaction, HRI has still many challenging aspects that are yet to be explored and investigated [Goodrich and Schultz, 2007]. The human-robot dialogue required for a peer collaboration where one human and robot work together is one of them [Fong et al., 2001, 2003; Mutlu et al., 2015]. Current research in human-robot dialogue explores its opportunities and challenges, but it has yet to agree on standards of human-robot dialogue due to contribution from multiple research communities including robotics, multi-modal interfaces, natural language processing, dialogue systems human-computer interaction and human-robot interaction [Mutlu et al., 2015]. We are still in the early stages of research on enabling dialogue for fluent human-robot interaction [Mutlu et al., 2015; Mutlu, 2011; Peltason and Wrede, 2011].

This chapter presents a survey of literature related to the research presented in this thesis and focuses on human-robot collaboration and human-robot communication.
2.1 Models of Human-Robot Interaction

During human-robot collaboration, a human and robot work together to make decisions about their joint actions. In this thesis, joint actions are those actions in which both the robot and the human communicate as a team to achieve a common goal [Hoffman and Breazeal, 2004].

As with two humans, human-robot team communication requires sharing information and taking initiative. The style of communication varies based on collaborative task, interaction, and environment.

The communication requirements for human and robot collaboration involving dialogue differ in types of shared tasks for human-robot interaction [Fong et al., 2001]. In their seminal work, Yanco and Drury [2002] categorized types of interactions in a taxonomy of human-robot interaction. The categories were based on autonomy level/amount of intervention, ratio of people to robots, and level of shared interaction among human-robot teams. The autonomy level indicates the robots’ level of autonomy, and the intervention level measures human intervention during a human-robot interaction. The authors suggest that the sum of robot autonomy and human intervention measurements should equal 100 percent. For instance, tele-operated robots have the least amount of autonomy (0 percent) and the greatest degree of human intervention (100 percent). On the other hand, museum tour-guide robots have full autonomy and require almost no human intervention [Nourbakhsh et al., 2005]. The ratio of people to robot does not measure the level of interaction but the quantity of interactions. Yanco and Drury [2002] classified the level of shared interaction among human-robot teams by the number of possible interactions, based on the level of control, as summarized below (Figure 2.1):

- A. one human, one robot: One human controls one robot.
- B. one human, robot team: One human controls a group of robots, issuing a command that the robots coordinate among themselves.
- C. one human, multiple robots: One human controls multiple individual robots,
issuing multiple individual commands to robots that operate independently.

- D. human team, one robot: Humans agree on robot commands and issue a coordinated command to a single robot.
- E. multiple humans, one robot: Humans issue different commands to a single robot that the robot must deconflict (i.e., resolve conflicts) and/or prioritize.
- F. human team, robot team: A team of humans issues a command to a team of robots. The robots coordinate which robot(s) performs which portion(s) of the command.
- G. human team, multiple robots: A team of humans issues one command per individual robot.
- H multiple humans, robot team: Individual humans issue different commands to a team of robots, which the robots must deconflict (i.e., resolve conflicts) and/or prioritize and divide among themselves.

Humans may interact with robots as a supervisor, operator, mechanic, peer or bystander [Scholtz, 2003]. Supervisory interaction is the same as when one human supervises another human. The interaction is monitoring robots and evaluating their actions to achieve some goal(s). Here the
robot software automatically generates actions. Supervisors, however, may step in to refine the robot’s planning system, goals, and intentions to achieve any desired goals. Operator interaction allows an operator to choose robot-appropriate control mechanisms, behavior, or takes over full control to tele-operate the robot using the software. Scholtz pointed out the fact that the operator cannot change the goal or intention. Thus interaction support is needed for action, perception, and evaluation levels. Mechanic interaction refers to the role in which a human physically changes robot hardware (e.g., fixing a camera). It is similar to an operator role except for the hardware part. When changes have been made, software and hardware need to be observed to validate the robot’s desired behavior that requires support for actions, perceptions, and evaluation. Bystander interaction refers to an implicit interaction with robots (e.g., interacting passively with Roomba, a home-cleaning robot, or museum tour guide robot). A robot might have some available controls for bystanders. The research on emotion and social interaction investigates how to make available robot capabilities evident to bystanders. The Peer interaction assumes that supervisors have control over only changing the goals and intentions. Then teammates can give commands to robots in order to achieve higher goals and intentions. For observations, we need support for the perception and evaluation levels. Human members interaction will not involve low-level robot behaviors (i.e., obstacle avoidance), but rather high-level behaviors (i.e., follow me). In case of emergency, a peer can take the role of operator or have the ability to hand off problems to a more qualified operator.

Human-robot interaction environments for during collaboration can be divided into two general categories based on a time/space matrix [Dix et al., 2004], based on when and where a human and a robot are working together: proximate interaction and remote interaction [Goodrich and Schultz, 2007]. Proximate interaction takes place when a human and robot are co-located in each other’s line of sight. Remote interaction is when a human and a robot are in different locations and not in each other’s line of sight. Human-robot interaction with social robot-assistance is considered as a proximate interaction since both human and robot are co-located and interacting face-to-face. Human-robot dialogue support during proximate interaction needs to consider both non-verbal
In contrast, a human-robot interaction during an urban search and rescue operation is considered a remote interaction since the human collaborator and robot are in different locations and out of sight of each other. Thus human-robot dialogue support for remote interaction does not necessarily require human-robot dialogue support for non-verbal cues but is primarily dependent on a rich dialogue that can aid shared decision making. The research in this thesis explores human-robot dialogue support for remote interaction during a search and rescue collaborative task scenario where communication is essential for a robot to work as a partner with a human collaborator.

Goodrich and Schultz [2007] argue that human-robot interaction (HRI) is a new and emerging field rather than an extension of previous work in human-computer interaction. In contrast, most early work in HRI began by taking ideas from HCI and applying them to human-robot environments. Human-robot interaction (HRI) studies the interactions and relationships between humans and robots. It is a multidisciplinary field. Scholtz identified the difference between human-robot interaction and computer-human or human-machine interaction along different dimensions: interaction with environment, robot’s dynamic nature, control of multiple robots, autonomy, and other levels of human interaction [Scholtz, 2003]. Unlike a traditional computer, mobile robots need to interact and adapt to the dynamic, chaotic, and uncertain nature of the physical environment. Such interaction may be as simple as calibrating sensor values due to changes in the environment.

![Diagram: Human-robot interactions must be considered from multiple perspectives (from Ferketic et al. [2006])](image)
Several researchers [Scholtz, 2003; Yanco et al., 2006; Yanco and Drury, 2002] have approached developing HRI frameworks by extending and modifying the existing model of HCI to describe HRI systems. Scholtz proposed five modified models based on Norman’s stage-action model of interaction for the various HRI roles.

Norman [1990] proposed seven stages of action as a model of human-computer interaction. The stages consist of: one stage for goals (e.g., forming the goal), three for execution (e.g., forming the intention, specifying the action, and executing the action), and three for evaluation (e.g., perceiving the state of the world, interpreting the state of the world, and evaluating the outcome). Norman also coined two important terms (gulf of execution and gulf of evaluation) that are valuable for understanding major user problems [Schneiderman, 1998]. The gulf of execution is the mismatch between user intentions and allowable actions. The gulf of evaluation is the mismatch between the system’s representation and the user’s expectations. Human-robot dialogue can play a role in both gulf of evaluation and gulf of execution by raising human awareness about a robot’s capabilities and providing feedback during events such as a malfunction.

Norman’s model suggests four principles of good design [Norman, 1990]. A well-designed system’s state and the action alternatives should be visible. The system should be based on a conceptual model with a consistent image. The interface should include mappings that reveal the relationships between stages. Finally, the user should receive continuous feedback. Norman’s formulation of stages of execution includes forming the goal, forming the intention, specifying an action and executing the action. Norman emphasizes studying errors. He describes how errors often occur in moving from goals to intentions to actions and to executions. His model can be adopted to recover from human-related errors during a human-robot collaborative task. For example, while collaborating with a robot in a search and rescue scenario, a human participant acting as a peer decomposes the search problem (i.e., goals), then generates a set of actions (i.e., intentions), and then asks the robot to execute an action (i.e., executions). An error may happen anywhere in this continuum. Monitoring user errors, providing feedback and employing dialogues allow the
peer robot to challenge or persuade human participants to avoid committing mistakes. Such actions can enhance task success rates and reduce human-related errors.

Drury et al. [2007] studied the possibilities of adapting the four different GOMS (Goals, Operators, Methods and Selection rules) elements to apply in human-robot interaction. The GOMS model predicts user behavior in unpredictable situations. Human-robot interaction interfaces are usually complex (e.g., urban search and rescue interface) where users need to make decisions about different objectives simultaneously. Drury et al. [2007] proposed new operators in order to handle the dynamic nature of human-robot interaction. Drury et al. [2007] also concluded that only a fragment of human-robot interaction could be implemented using the GOMS model. In my research, the impact of integrating human-robot dialogue support for shared-decision making is explored.

The list of HRI theories discussed here is by no means exhaustive. It merely describes the most cited recent work and suggests further research. Recent research in human-robot interaction looks into modeling human users while interacting with robots and concludes that due to the nature of interaction and application HCI models need to be modified or extended before being applied to HRI. It is evident that different interactions present different design questions. Identifying these questions is one of the many goals of ongoing human-robot interaction research.

Adams has identified different areas of human factors research such as human decision-making, workload, vigilance, situation awareness, and human error [Adams, 2002]. Situational awareness requires robots to communicate relevant information to human to understand what is occurring in the robot’s world [Scholtz, 2003]. While designing effective interfaces for robots, we need to understand the possible interactions in the domain of human-robot interaction. Interaction differs from domain to domain. Robotics interface design may vary based on the different interactions users have with them. For instance, in an urban search and rescue scenario, users usually control a semi-autonomous robot (e.g., obstacle avoidance behavior). Rescue robots need user involvement identifying victims or navigating a dynamic, chaotic environment resolving conflicts and robot er-
rors. It is critical to include communication features (e.g., dialogue) in the system to communicate effectively and locate victims in time-constrained rescue scenarios [Yanco et al., 2006]. In contrast, a cost-effective floor-cleaning robot with minimal intelligence can operate without providing situational awareness information to the human.

2.2 Human-Robot Dialogue

Generating human-robot dialogue, like Natural Language Generation (NLG) [Lemon, 2011], requires determining “what to say” before deciding “how to say it”. The “what to say” problem addresses ways to determine the content of plausible dialogue during human-robot interaction. The “how to say it” problem addresses the best ways for a robot to deliver that content (e.g., using text, gestures, speech or different modalities). The “what to say” problem can be further categorized into two major categories, namely what “concepts” to convey and what “words” to use to express those concepts. The “when to say it” problem addresses the timing of dialogue delivery (e.g., turn-taking). This section first discusses the research in Human-Robot Dialogue that addresses the three major problem categories: the “how to say it,” “when to say it,” and “what to say” problems, followed by other related issues.

2.2.1 Human-Robot Dialogue Delivery: How to say it

A human-robot collaboration that requires proximate interaction such as face-to-face interaction needs to address the “how to say it” problem. The research on embodied cues for dialogue with robots delves into the delivery of human-robot dialogue, which we refer to as the “how to say it” problem [Mutlu, 2011; Simmons et al., 2011].

Mutlu et al. [2006] and colleague investigated how a robot’s gaze cues might be manipulated to achieve learning outcomes in participants. In this study two participants listened to a story told by Honda’s ASIMO human-like robot. The robot’s gaze behavior followed a partly stochastic,
partly rule-based, data-driven model of a gaze developed to achieve human-like gaze shifts that accompany speech. This study tested the hypotheses that increased gaze would increase participant recall of story detail and improve the participants’ overall evaluation of the robot. Twenty college students (12 males and 8 females) participated in the first study for ten different sessions. The results of their study verified the relationship between gaze cues and learning outcomes. It also showed strong gender effects on this relationship. Increased robot gaze improved information recall in females, but not in males. On the other hand, increased gaze decreased favorability of female evaluations of the robot, but it did not affect males evaluations. In their research, Mutlu et al. [2006] explored only dialogue delivery problem.

Mutlu [2011] investigated how embodied cues such as a gaze, facial expression, head gesture, posture, arm gesture, social touch, social smile, or verbal or vocal cue might achieve positive outcomes, including improved attention, learning, rapport, compliance, or persuasion, in embodied human-robot interaction. The studies were designed by observing human behaviors as well as studying existing research on human communication. Mutlu [2011] argued that embodied interaction is fundamentally a joint activity in which the embodied cues of all parties in the interaction work together. Future research in the delivery of human-robot dialogue problem should also look into how various characteristics of context affect embodied interaction. Also, we need to have a better understanding of how a robot might adapt their use of embodied cues across contexts to maximize their effect in achieving social, cognitive, and task outcomes. Lastly, the development of effective embodied cues for human-robot dialogue must examine how joint use of cues by humans and robots might evolve and co-adapt and what techniques might best model these temporal, interdependent changes in behaviors. While the research in the adaptive embodied cues of robots explores the human-robot delivery problem, the research in adaptive dialogue for human-robot interaction explores generating dialogue content based on user expertise and is discussed in this chapter.

Valerie the Roboceptionist, a widely cited social robot project, investigated believable robot
characters by designing a robot-receptionist. Valerie was designed to investigate long-term human-robot social interaction to transition robots from the lab to the real world [Kirby et al., 2005]. The believability of the robot-receptionist was achieved by character design with a rich backstory and evolving storyline, verbal and non-verbal social behaviors, and believable cultural characters that incorporated ideas from literature, theater, film and animation [Simmons et al., 2011]. Designing verbal and non-verbal behaviors for the robot-receptionist can be categorized as a “how to say it” problem. The robot performed as several characters in different situations, and the human participants had the option of deciding whether to interact with the robot. The human-subject communicated with the robot by typing on the keyboard. All robot dialogues were scripted and spoken in a voice generated by text-to-speech software. The robot-receptionist greeted, provided information, such as directions to offices, and talked about her “life.” Interactions between Valerie the Roboreceptionist and human visitors of Newell-Simon Hall at Carnegie Mellon University over the first nine months of the operation (a total of 180 days) were analyzed to investigate whether believable robot characters would be engaging and attract people [Kirby et al., 2005]. The objective results indicated that over 200 individual human visitors had bonding relationships with the robot-receptionist and interacted with her for more than 30 seconds on a daily basis. The research found that dialogue support for “turn-taking” (discussed in the next section) would have improved human-robot interaction. Although the influence of the robot-receptionist’s appearance was minimal, the robot’s occupation and background story played an important role establishing common ground between a human user and the robot-receptionist. The analysis of long-term human-robot interaction concluded that a successful human-robot interaction needed to meet user expectations with respect to natural language understanding and generation capabilities, intentionality of verbal and nonverbal behaviors, robot autonomy, and awareness of sociocultural context.
2.2.2 Human-Robot Dialogue Timing: When to say it

*Turn-taking* is the challenge of figuring out which partner has the floor to speak or act during conversation and can be categorized as a “when to say it” problem. “When to say it” problems address the timing of human-robot dialogue delivery. Thomaz and Chao [2011] explored the turn-taking aspects of human-robot communication, proposing a turn-taking framework for human-robot communication. In this framework, the turn dynamics are characterized as *partially observable* to address the problem of figuring out which partner has the floor to speak or act. Their framework also provided a turn-taking model, which was a domain-specific FSM (finite state machine) that could generate parameterized action (e.g., speech, gaze, gesture and manipulation) to create a domain-independent turn-taking module. A pilot study was conducted involving eight human-participants with a 38-DOF (38 degree-of-freedom) upper-torso humanoid social robotic platform called “Simon”, demonstrating the benefits of an architecture designed especially for turn-taking with humans and robots in human-robot collaborative scenarios.

In the *visitor companion* task scenario, a robot may guide a human visitor on an unfamiliar tour while, at the same time, the human helps the robot with capabilities the robot lacks. Both the robot and the human together have capabilities to complete the task. The visitor companion robot, CoBOT, developed by [Rosenthal et al., 2010] asks the human questions when it needs help. The research explored “when to ask” to gain human help during a collaborative task, which is different from “turn-taking,” since it addressed the problem of figuring out the appropriate time for a robot to ask the human collaborator a question. In addition, the visitor companion robot, CoBOT also had to address where to ask for human help during navigation. For example, a visitor companion robot might need human help to push an elevator button to call an elevator. Rosenthal et al. [2010] conducted a study of subjective experience in which visitors were being helped by CoBOT with directions to meetings and on occasion requests for coffee or other minor tasks. The results from five visitors suggests that a robot asking human companions for help reduced localization uncertainty and established a better relationship between humans and the robot. Visitor
companion tasks are an example of a joint task where the human and the robot have to work together to achieve their goals. A search-and-rescue task also involves a joint task where the robot is in the field while the human is working with the robot behind a computer in a separate location. Each has to depend on the other to complete the task. Joint task scenarios require a set up in which collaborators can discuss and share decisions or ask each other’s help when needed.

### 2.2.3 Human-Robot Dialogue Content: What to say

Krestin [2011] has studied how robot dialogue can be designed to reduce uncertainty about joint tasks and robot capabilities. The results of an experiment involving 22 human participants confirmed that the content of feedback (e.g., a “what to say” problem) positively affects human-robot interaction by lowering user uncertainty during interaction. [Krestin, 2011] concluded that user expectations of robot capabilities and appearance affect not only human-robot relationships but also human-robot dialogues. Krestin [2011], however, employed a Wizard-of-Oz methodology without demonstrating how effective dialogues could be generated.

Chidambaram et al. [2012] explored how a robot might improve the persuasiveness of its messages using verbal cues, particularly linguistic markers of expertise. The human participants interacted with a Mitsubishi Wakamaru Robot. The study tested two hypotheses: (i) participants would express a stronger preference toward options presented using expert language than they do toward options presented using non-expert language; (ii) the persuasion outcome would be stronger for women than it would be for men in the study. Twenty-six college students (16 males and 10 females whose ages ranged from 19 to 28), all native English speakers, participated. During the study, the participants constructed a walking map in a fictional city and listened to information from the Wakamaru Robot on the alternative landmarks that they could visit. At every intersection, the robot provided information on two similar landmarks (e.g., two amusement parks), using linguistic markers of expert speech with one and those of non-expert speech with the other. The results of the study confirmed the first hypothesis. The study also supported the prediction that
verbal cues of expertise increased the persuasiveness of the information that the robot provided and affected participant preferences. Men and women were equally affected by these cues, but the cues had stronger effects overall on women. This study showed the effectiveness of verbal cues of expertise in crafting persuasive messages and showed the potential benefit of developing a model of expert speech for robots. Chidambaram et al. [2012], however, did not explore how either humans or robots engage in dialogue to persuade each other to alter each other’s beliefs.

Analyzing and categorizing different dialogue types used by a social robot and human participants over an extended period of time in a social setting can contribute to the “what to say” problems of designing a dialogue system and modeling adaptive dialogue based on a user’s expertise. The dialogue content between Valerie the robot receptionist and 197 human participants over five days were analyzed to investigate the types of dialogues used by human participants [Lee and Makatchev, 2009]. The results indicated that 41.54% of those dialogues were task-specific questions (e.g., location of offices or where to get a taxi) and related to seeking information. About 30% of the dialogues were related to chatting about the robot, 20% of the dialogues were related to greetings (i.e., saying hello), and 10% of the dialogues related to impolite behaviors (i.e., insulting the robot). The results of this dialogue analysis derived from an objective analysis of system data and did not employ subjective analysis from user surveys. In addition, unlike the research presented in this thesis, dialogue types were manually categorized since the robot-receptionist employed scripted dialogue and did not employ any dialogue framework or dialogue rules or user surveys.

Research in adaptive robot-dialogue addresses issues of designing and generating robot-dialogue to achieve effective natural language communication based on a users’ level of experience during human-robot collaboration [Torrey et al., 2006, 2009]. In their earlier work, they investigated the impact of adaptive dialogue by comparing a robot using the adaptive dialogue mode to with a robot without it. In their 2x2 (expertise × dialogue) experimental design, the experimenters categorized human participants as novices or experts. The experimenters employed an online test before partic-
ipation that indicated to the robot system through a series of queries whether the human participant was an expert or novice. A robot primarily designed for nursing home use was adopted to serve as a stationary chef robot and with a male voice instructed novice or expert cooks how to make creme brulee. It responded to the users’ typed input by employing conversational grounding theoretical framework [Schober and Brennan, 2003] for spoken discourse in natural language processing. The chef-robot used Cepstral’s Theta, a text-to-speech-synthesizer [Cepstral, 2004] for speech synthesis, and the text appeared on the screen in an interface similar to Instant Messenger. The robot interpreted and responded to the participant’s input using a customized variant of Artificial Intelligence Mark-up Language (AIML). In their first experiment, two experimental conditions were employed. The robot asked the human participants to identify ten cooking tools while collaborating in baking creme brulee. In the first experimental condition, “Names Only,” the robot provided participants with limited descriptive information to identify cooking tools. In the second experimental condition, “Names Plus Description,” the robot provided more descriptive information to identify cooking tools. In the first experiment, information exchange and social relations were measured from data collected from 49 participants to test two hypotheses. The first hypothesis predicted that the additional descriptive information would not benefit the performance of the experts but would benefit the performance of the novice users. The second hypothesis predicted that additional descriptive information would be favored more by novice users than expert users. Each participant was either a student or staff members of Carnegie Mellon University (CMU). Participants had no prior experience with the experiment but were paid. A measurement of social relations included the user’s perspective on the robot’s authoritativeness, responsiveness, conversational control, conversational effectiveness, task difficulty, and how enjoyable the task was. The results of the first experiment confirmed the first hypothesis that the system performance of novices would benefit from additional descriptive information, while the second hypothesis about the subjective effect of social relations on human-robot interaction proved to be inconclusive.

Torrey et al. [2006] conducted a second experiment nearly identical to their first, but partic-
ipants received monetary incentives for completing the task fast while accurately identifying the cooking tools. The experiment’s purpose was to investigate the second hypothesis about the effect of social relations on human-robot interaction with 48 new participants. Additional description was added in the “Names Plus Description” mode for three cooking tools, which were most mis-identified during experiment 1. Also, eight questions were added to the post-experiment questionnaire to assess the concept of patronizing (e.g., my partner’s explanation is condescending) and content appropriateness (e.g., I got just the right amount of information). As in experiment 1, participants were students or staff members of CMU and were paid $8 with additional bonuses of up to $15 for their performance in the second experiment. The results from their second experiment confirmed that adaptive robot dialogue could improve robot relations with both expert and novice human users who are pressured for time. Torrey et al. [2006] concluded that robots with diverse needs that interacted with humans face-to-face through a speech-only interface would be more productive and effective if these robots could assess and adapt to the expertise of human users.

[Tellex et al., 2011] proposed a framework called Generalized Grounding Graphs ($G^3$), which can map the connections between the spoken language and spatial references to the external world (e.g., objects, places and events). The $G^3$ framework facilitates learning word meanings from data. Although the model performed well in the experiment, Tellex et al. [2011] argue that the ability to understand spatial language discourse and engage in dialogue is crucial for robust human-robot interaction. Grounding graphs provide a framework that begins to address these problems but still are incapable of handling more complex conditional expressions (e.g., if a truck comes in, unload it) or converting high-level commands into series of low-level commands (e.g., drive forward six feet).

The research in multi-modal dialogues investigates the challenges of developing a human-robot interaction system that can support multi-modal dialogue. Those dialogues, which may involve fusing speech, gesture or gaze, require complex co-ordination among speech-recognition, visual-detection and human-tracking systems. Various robots have also been developed that respond to

TeamTalk [Marge et al., 2009], a multi-modal human-robot interface, was designed to interpret spoken-dialogue interactions as well as mouse clicks and pen gestures between humans and robots to perform tasks associated with treasure hunting. The Olympus Spoken dialog-framework [Bohus et al., 2007] was used to implement TeamTalk’s speech component. The system consisted of all the processes that are necessary to maintain a task-based dialog with a human user. It used a Logios language model-building component that was used to automatically create a dictionary and language model based on the English grammar. The Phoenix server parsed decoded speech using a context-free grammar. A dialogue manager modeled the state of dialogue conversation between conversing parties at each step of the interaction and tracked the next task that the robot should perform. The backend of TeamTalk communicated with robots involved in various tasks. It was deployed in the controlled Treasure Hunt search domain where a human-robot team received tasks to locate “treasures” (e.g., color-coded objects) that were scattered throughout an indoor area in a newly developed virtual platform based on an open source robot simulation environment, USARSim. USARSim was primarily designed to support educational research and evaluation for remote urban search-and-rescue robot scenarios [Carpin et al., 2007]. TeamTalk was further extended as a framework to support multi-human-robot dialogue research for multi-human multi-robot team that aided rapid-prototyping and remote collaboration, enabling spoken language and map-based interactions for both physical and virtual robots [Harris and Rudnicky, 2007].

Museum robots [Thrun et al., 2000] and robot receptionists [Kirby et al., 2005] are just a few examples of many existing HRI systems that use scripted dialogue management modules. A scripted dialogue model generates dialogue based on a pre-determined task (e.g., museum tour guide, shopping mall guide), but does not scale for robots (e.g., rescue or team robots) that operate in a highly dynamic and changing environment (e.g., rescue arena) where humans and robots work
together to achieve a common goal.

[Scheutz et al., 2011] demonstrated the challenges faced by natural language parsers for robotics systems. The authors categorized six properties of natural language processing (NLP) for robots: real-time, parallel, spoken, embodied, situated, and dialogue-based. One of the challenges of NLP parsers for robotics is that they require a large corpus of data, which is lacking in the domain of human-robot collaboration, to train the system. Although a natural language dialogue model is a plausible approach in some contexts, it does not yet address many human-robot dialogue problems due to a lack of feasible NLP solutions.

Humans are most comfortable interacting with human-like agents, and implementing human-like characteristics is a gateway to more effective human-robot interaction [Bernstein et al., 2007]. Users need to have accurate models of complex technology. To improve human-robot interaction, [Bernstein et al., 2007] proposed three design guidelines: diagnostic transparency, predictive transparency, and simplicity. Diagnostic transparency refers to user ability to figure out why a robot is not behaving as desired. It allows users to accurately establish behavioral causality simply by observing the robot. Predictive transparency helps us figure out what a robot will do next. Simplicity enhances diagnostic and predictive transparency because it is easier to create a model of a simple robot than a complex one. Well-designed dialogue during human-robot communication can reduce user uncertainty and increase diagnostic and predictive transparency [Krestin, 2011]. My research presented in this thesis investigates the issues related to generating the content of effective human-robot dialogue to share or expand knowledge and resolve conflicts by challenging and persuading during peer collaboration.

2.3 Models of Collaboration

The Human-Robot Interaction Operating System (HRI/OS) [Fong et al., 2006b], an interaction infrastructure based on a collaborative control model [Fong et al., 2001], was introduced to provide a framework for humans and robots to work together. The software framework supported human
and robot engagement in a task-oriented dialogue about each others’ abilities, goals, and achievements. HRI/OS was designed to support the performance of operational tasks, where tasks were well-defined and narrow in scope. In space exploration, operational tasks include: shelter and work hangar construction, habitat inspection, and in-situ resource collection and transport. HRI/OS is an agent-based system that incorporates embodied agents (humans and robots) and software agents employing a goal-oriented Open Agent Architecture for inter-agent communication and delegation [Cohen et al., 1994]. The Open Agent Architecture (OAA) [Cohen et al., 1994] introduces the Inter-agent Communication Language (ICL) for interface, communication, and task coordination using a language shared by all agents [Cohen et al., 1994] regardless of platform and the low-level languages in which they are programmed. Fong et al. [2006b] have identified robots as capable of resolving issues, rather than immediately reporting task failure, through dialogue with humans in cases where robots lack skills or their resources have proved inadequate to the task. For example, a robot that has difficulty interpreting camera data might ask a human to lend visual processing ability to the task. This often allows tasks to be completed in spite of limitations of autonomy. Fong et al. [2005] have investigated how peer interaction can help communication and collaboration, and the authors concluded that engaging in a dialogue where robots can ask task-oriented questions of humans through remote interaction such as teleoperation can be beneficial.

Researchers have also looked into planning to aid collaboration. Planning is difficult as things regularly change in the robot’s world and plans fail. The idea of a shared plan uses complex actions and partial plans and models the possibility that agents will contract out actions to other agents. A full shared plan (FSP) is a complete plan in which agents have fully determined how they will perform an action. A partial shared plan (PSP) provides a specification of the minimal mental-state requirements for collaboration and gives criteria that govern the process for completing the plan. A full recipe for undertaking an action A (alpha) is the set of actions and constraints that constitute the doing of A (alpha). A partial recipe is a set of actions that can be extended to a full recipe [Grosz
et al., 1999]. Shared plan theory considers agent capabilities and agents’ willingness to commit to
a plan. Grosz et al. [1999] formalized planning and action, distinguishing (1) an intention to carry
on an action and (2) an assumption that a proposition would hold. An agent intending to act: must
be committed to undertaking an action; it must have appropriate beliefs about its ability to carry
out the action; and it must have the knowledge to do it or learn how to do it.

Grosz and Kraus’ shared plan theory [Grosz and Kraus, 1996, 1999] provides the following:

- a minimal collective mental state is required for a group of agents to have a plan for collab-
  orative activity,

- constraints on agents’ beliefs and intentions as they initiate and expand partial plans,

- stopping conditions for planning processes, and

- means of representing the commitments of participants in collaborations.

[Rich et al., 1998] proposed Collagen, an application-independent collaboration manager that
based on a shared plan theory of discourse supports the user’s problem-solving processes. Rich
et al. [1998] argued that successful collaboration depends on each agent knowing what to do next?
Collagen used a shared plan in the context of discourse. The shared plan was designed to provide a
Natural Language Processing solution for keeping track of what has been done and what needs to
be done in a collaborative task. It does not necessarily include dialogue but provides dialogue can-
didates that can be sorted by the dialogue manager or planner. TRAINS is an end-to-end real-time
spoken dialogue system that integrates natural language understanding. It can be used to develop
a conversationally proficient intelligent planning assistant agent that can engage in dialogue with
a human to find a shared plan [Allen et al., 1995, 2000]. Shared plan research is in the domain of
planning a joint task. It addresses the challenges that agents face in collaborating on a task. Shared
plan research can aid group decision making algorithms and problems around how to collaborate
effectively.
Joint intention theory [Cohen and Levesque, 1991] explores and theorizes the motivation of agents working together as a team. Cohen and Levesque [1991] argues that “a joint activity is one that is performed by individuals sharing certain specific mental properties.”

Research in collaborative learning addresses issues related to how a robot can independently learn new task collaborating with a human. Breazeal et al. [2004] employed joint intention theory [Breazeal et al., 2004] to provide collaborative support for humans to teach tasks to a robot and establish a common ground for learning and collaboration. Recently, Kartoun et al. [2010] addressed the problem of collaborative learning between a robot and a human by developing a new reinforcement learning algorithm that utilized human expertise and intelligence to maximize team performance. Epstein [1994] developed a domain independent cognitive architecture called FORR (FOr the Right Reasons). It addresses learning and problem solving for automated knowledge acquisition by modeling it after the development of human expertise. Recently, FORR [Epstein, 1994] has been applied as cognitive architecture in a human-robot collaborative system to support shared decision making [Epstein et al., 2012]. Recently, Rosenfeld et al. [2015] presented the design and evaluation of an intelligent automated system that employed an optimization model designed to enhance human operator performance. It selected when and which advice to provide in a greedy fashion during human-multi-robot team collaboration in search and rescue environments. Rosenfeld et al. [2015], however, did not address dialogue related issues in their research. Instead, the research focused on designing automated intelligent agents to act as supplemental help when a human is working with more than one robot.

The research presented in this thesis focuses on investigating issues related to human-robot dialogue in the context of peer and supervisory interaction and leaves the exploration of collaborative control model for future work.
Chapter 3

Background

An extension of existing argumentation-based dialogue theory, ArgHRI, is developed in this thesis to support peer interaction, for the human-robot collaboration that shares decision making. Argumentation-based Dialogue is based on Argumentation theory [Bondarenko et al., 1997; Nielsen and Parsons, 2006], which that can be used to evaluate the acceptability of an argument for resolving conflicts during collaborative decision making. This research adopted the formal system from [Parsons et al., 2003a, 2007], as detailed in [Sklar and Azhar, 2015]. An extension of existing argumentation-based dialogue theory, ArgHRI, is developed in this thesis to support peer interaction for human-robot collaborative decision making. Section 3.1 provides the essential technical background on argumentation theory required to demonstrate how argumentation-based dialogue can be employed to extend current HRI capabilities. Section 3.2 describes the theoretical background for argumentation-based dialogue. Section 3.3 discusses current research in the applications of argumentation-based dialogues.

3.1 Argumentation Theory

Argumentation is a reasoning mechanism modeled after human argumentation, deriving reasoning semantics by analyzing the support and defeats of arguments [Walton and Krabbe, 1995]. An
argument is a logical entity that represents both a conclusion and the evidence supporting that conclusion. *Defeat* detects the contradictions between arguments.

An **Argumentation System** [Amgoud et al., 2000] formally consists of:

- $\text{Ags} = Ag_1, Ag_2...$ where each $Ag_i$ represents an agent

- $Ag_i, \Sigma$ is the knowledge base, or set of beliefs, for each agent, where $\Sigma$ consists of formulae written in the logic language, $L$. $L$ is a propositional language consisting of atomic propositions, $p$, which are individually either true or false. An inference mechanism $\vdash_L$ is associated with $L$ such that

$$S \vdash_L c$$

which means that $c$ can be proven from $S$ using rules and propositions contained in the language $L$. A rule

$$p_1 \land p_2 \land \ldots \land p_n \rightarrow c$$

derives, or proves, an agent’s conclusion $c$ when every $p_i$ listed in the rule is either a member of $\Sigma$, or can be derived as the conclusion of another member of $\Sigma$. In theory, $\Sigma$ is allowed to be inconsistent, but some systems require $\Sigma$ to be consistent; in other words, $\Sigma$ can not contain both $p$ and $\neg p$.

- An **Argument** $A$ is a pair $\langle S, c \rangle$ where $S$ is the support for the argument, $\{p_1, p_2, \ldots, p_n\} \in S$ and $c$ is the conclusion of the argument. $c$ and $S = \{s_1, s_2, \ldots, s_n\}$ are formulae $L$ and $S$ is a subset of $\Sigma$ such that:

1. $S$ is consistent;
2. $S \vdash_L c$; and
3. $S$ is minimal, meaning that no proper subset of $S$ satisfying both (1) and (2) exists.

$S$ is called the **support** of $A$; and $c$ is the **conclusion** of $A$. 
In theory, Arguments in $\mathcal{A}(\Sigma)$ may conflict since $\Sigma$ may be inconsistent where $\mathcal{A}(\Sigma)$ denotes the set of all possible arguments that can be made from $\Sigma$. Conflicts are also attack relations between arguments, as illustrated in Figure 3.1 and 3.2.

Figure 3.1: Forms of attack between arguments: $c_1$ rebuts $c_2$, and, symmetrically, $c_2$ rebuts $c_1$; $c_1$ undermines $S_2$; and $c_2$ undermines $S_1$ [Sklar and Azhar, 2015].

We identify the following two ways in which arguments may conflict:

- **rebuttal**: $\{S_1, \neg c\}$ rebuts $\{S_2, c\}$ where the conclusion $\neg c$ of one argument $S_1$ conflicts with the conclusion $c$ of another argument $S_2$. An argument $A_1=\{S_1, c\}$ defeats another argument $A_2=\{S_1, \neg c\}$ if $\{S_1, \neg c\}$ rebuts $\{S_2, c\}$.

- **undermining**: $\{S_1, \neg P\}$ premise undercuts $\{S_2, c\}$ where $P \in S_2$. Here the conclusion $c$ of one argument $S_2$ conflicts with some element $\neg P$ in the support of another argument $S_1$. An argument $A_1=\{S_1, c\}$ defeats another argument $A_2=\{S_1, \neg c\}$ if $\{S_1, \neg P\}$ undermines $\{S_2, c\}$.

- Arguments can also support each other. We identify two ways in which arguments may offer support [Sklar and Azhar, 2015]
  
  - **premise-support** ($p$-support)—where one argument is part of the support for another argument; and
  
  - **conclusion-support** ($c$-support)—where two non-intersecting sets of propositions support the same conclusion.
Let us consider the following argument \( \text{Arg}_1(S, c) \) where \( \{p_1 \land p_2\} \in S \)

1. \( p_0 = \text{“Robot should go to room that are close by”} \)
2. \( p_1 = \text{“Robot is in room 1”} \)
3. \( p_2 = \text{“Room 1 is close to room 2”} \)
4. \( c = \text{“Go to room 2”} \)

Let us consider another argument \( \text{Arg}_2(S, c) \) where \( \{p_3\} \in S \)

1. \( p_3 = \text{“The entry to room 2 is blocked”} \)
2. \( \neg c = \text{“Don’t go to room 2”} \)

Thus, \( \text{Arg}_2(S, \neg c) \) \textbf{rebuts} \( \text{Arg}_1(S, c) \)

Figure 3.2: An example of \textit{rebuttal}

These are illustrated in Figure 3.3.

Figure 3.3: Forms of \textbf{support} between arguments: \( c_1 \in S_2 \) and thus \( p \)-supports \( c_2 \); \( c_2 \in S_1 \) and thus \( p \)-supports \( c_1 \); \( S_1' \) \textbf{c-supports} \( c_1 \), where \( S_1 \cap S_1' = \emptyset \) [Sklar and Azhar, 2015].

### 3.2 Argumentation-based Dialogue Theory

A dialogue theory needs to provide mechanisms for “how conversations start, proceed, and conclude [Ginzburg and Fernández, 2010]”. In the \textbf{argumentation-based dialogue} theory adopted in this research, a human and robot participate in a structured interaction following a set of protocols that decides the beginning, continuation, and termination of the dialogue [Sklar and Azhar, 2015]. According to argumentation theorists Walton and Krabbe [1995], there are six primary
types of human dialogue based on participants’ knowledge, individual and shared goals, namely:
(1) information-seeking dialogues, (2) inquiry dialogues, (3) persuasion dialogues, (4) negotiation
dialogues, (5) deliberation dialogues and (6) eristic dialogues. There are other types of human
dialogue found in the literature that include information-provision dialogues [McBurney and Par-
sons, 2005], verification dialogues [Cogan et al., 2005], and command dialogues [Atkinson et al.,
2009]. This research employed information-seeking dialogues, inquiry dialogues, and persuasion
dialogues, and they are briefly described below and described in detail in Section 4.

1. **Information-seeking dialogues:** One participant seeks answers to questions from another
participant, who is believed by the first participant to know the answers.

2. **Inquiry dialogues:** The participants collaborate to answer a question or questions whose
answers are not known to any participant.

3. **Persuasion dialogues:** One participant seeks to persuade another party with a different
opinion to adopt a belief or point-of-view.

<table>
<thead>
<tr>
<th>Type</th>
<th>Initial Situation</th>
<th>Main Goal</th>
<th>Participant’s Aims</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Persuasion</strong></td>
<td>Conflicting Points of view</td>
<td>Resolution of such Conflicts by Verbal Means</td>
<td>Persuade the other(s)</td>
</tr>
<tr>
<td><strong>Negotiation</strong></td>
<td>Conflict of Interests and Need for Cooperation</td>
<td>Making a Deal</td>
<td>Get the Best out of It for Oneself</td>
</tr>
<tr>
<td><strong>Inquiry</strong></td>
<td>General Ignorance</td>
<td>Growth of Knowledge and Agreement</td>
<td>Find a “Proof” or Destroy One</td>
</tr>
<tr>
<td><strong>Deliberation</strong></td>
<td>Need for Action</td>
<td>Reach a Decision</td>
<td>Influence Outcome</td>
</tr>
<tr>
<td><strong>Information-Seeking</strong></td>
<td>Personal Ignorance</td>
<td>Spreading Knowledge and Revealing positions</td>
<td>Gain, Pass on, Show, or Hide Personal Knowledge</td>
</tr>
<tr>
<td><strong>Eristics</strong></td>
<td>Conflict and Antagonism</td>
<td>Reaching a (Provisional)</td>
<td>Strike the Other Party and Win the Eyes of Onlookers</td>
</tr>
</tbody>
</table>

Table 3.1: Types of dialogue [Walton and Krabbe, 1995] (page 66).

Based on these six types of dialogues, multi-agent researchers have investigated how to repre-
sent human dialogues using a formal model of argumentation in order to support agent-agent com-
munication. The research presented in this thesis extends this basic idea to human-robot interac-
tion, as shown in later chapters. First, in this chapter, the fundamental concepts of argumentation-based dialogue theory are reviewed.

### 3.3 Applications of Argumentation-based Dialogues

Argumentation theory [Nielsen and Parsons, 2006] can be applied to provide support for a query or simple dialogue that can aid the diagnosis of robot errors from hardware, software, or changes in the environment in addition to resolving conflicts. Plan-based dialogue models have been developed using a belief, desire, and intention (BDI) architecture [Wobcke et al., 2005] in the agent-oriented software engineering community. Argumentation-based dialogue theory has been studied by researchers from Law, Artificial Intelligence, and multi-agent systems [Bench-Capon and Dunne, 2007; Medellin-Gasque, 2013].

Argumentation-based dialogues have been developed to help two agents to make decisions about their goals and plans. Black and Hunter [2009] developed a theoretical framework for two collaborative agents to engage in an inquiry dialogue to expand their knowledge. In her thesis work, Black [2007] demonstrated how this general framework can be applied in the medical domain where two doctors can be engaged in inquiry dialogues to expand their knowledge and make better decisions.

Two co-operative agents who share a goal will only accept plans that are aligned with their beliefs. Belesirotis et al. [2010] developed an abstract argumentation-based protocol that allows two such agents to discuss their proposals until an agreement is reached through the persuasion-aligning planning beliefs of those two agent. Black and Atkinson [2011] developed a dialogue framework where two agents employing persuasive dialogue can discuss how to act.

In their earlier work, Tang and Parsons [2005, 2006] developed formal mechanisms to employ argumentation-based deliberation dialogues. In those dialogues agents decide what actions to undertake and the order in which the actions should be performed, combining both agents’ knowledge and overlapping expertise. In their later work, Tang et al. [2010b] developed a formal
argumentation model to generate plans for a team that operates in a non-deterministic environment. Medellin-Gasque et al. [2012] developed a formal argumentation model for two common goal-sharing autonomous agents. In it they decide on a plan in which they will propose, justify, and share information about plans, engaging in argumentation-based persuasion and negotiation dialogue.

[Tang et al., 2010a, 2011b, 2012b] implemented an interface engine called ArgTrust, which is based on a formal argumentation framework for two agents to reason about their trust and beliefs. Recently, [Sklar et al., 2015] evaluated a prototypical version of the ArgTrust to study how people reason and make decisions in uncertain situations and how they explain their decisions. The results of the user study involving 22 participants indicate that an argumentation-based system such as ArgTrust can help humans carefully examine their decisions. This ArgTrust engine has been utilized for the research presented in this thesis described in Chapter 5.

In earlier work that extended the education dialogue system of Sklar and Parsons [Sklar and Parsons, 2004], we explored the application of argumentation dialogues to an Interactive Learning System (ILS) [Sklar and Azhar, 2011]. We proposed ArgILS, a general framework for an interactive learning system in which interactions between a Tutor and a Learner can be modeled using argumentation.

In this research, a model of argumentation-based dialogue on top of the discussed argument system that can support such human-agent communication is adopted from [Parsons and McBurney, 2003], who were influenced by the seminal work of [Walton and Krabbe, 1995]. Their research involved two agents that participated in a structured interaction following a set of dialogue protocols. Argumentation theory, however, has yet to be applied to generating dialogue in the domain of human and robot collaboration.

As far I am aware, the work presented in this thesis is the first to apply logic-based argumentation-dialogue for human-robot collaboration.
Chapter 4

Approaches and Methodology

In this chapter, I present our argumentation-based dialogue game approach and an argumentation-based dialogue framework for human-robot collaboration [Azhar, 2012; Sklar et al., 2013b; Sklar and Azhar, 2015]. Our approach enables the robot and the human collaborator to expand and share knowledge and make decisions together during human-robot collaboration. An argumentation-based dialogue game approach is applied to support a dynamic, evidence-backed exchange of ideas using dialogue to facilitate flexible interactions between a robot and human collaborator.

This chapter is structured as follows: Section 4.2 details a methodology for implementing multiple types of argumentation-based dialogues for human-robot interaction (HRI). It includes an explanation about which types of dialogues are appropriate given the beliefs of the participants. Section 4.1 outlines the key components of our proposed argumentation-based dialogue framework, ArgHRI, which supports collaboration between a robot and a human. Section 4.2.1 discusses dialogue protocols, which define the required opening, intermediate, and termination locutions or utterances for persuasion, inquiry and information-seeking dialogue. Section 4.2.2 details the axiomatic semantics, which specify how the execution of locutions in an argumentation dialogue, following the rules of the protocol, changes the states of the system. Section 4.2.3 provides a description of a control layer (CL) that can start, end and manage multiple dialogues while maintaining a consistent set of beliefs for the participants. Section 4.3 describes our experimental
domain and Section 4.4 details our experimental methodology.

4.1 The ArgHRI framework

Our ArgHRI framework is comprised of several components: an ontology that describes the robot’s environment and capabilities (domain dependent), a memory system for the robot to maintain its beliefs (domain independent), an argumentation engine that supports the robot’s internal decision-making (domain independent), and a dialogue system for interacting with a human (domain independent).

4.1.1 Ontology

We begin by introducing a simplified ontology that describes the robot’s actions and capabilities. This ontology includes a set of predicates that describe the robot’s actions and capabilities, its internal state, and the state of its environment (which includes the human). This ontology can be modified to support additional robot features.

The following predicates describe actions that the robot can perform:

- **GoTo**\((t, loc)\), where \(t\) is the time at which the action begins, \(loc\) is a location (e.g., \((x, y)\) co-ordinates) in the robot’s environment.
- **Stop**\((t)\), where \(t\) is the time at which the robot ceases motion.
- **Sense**\((t)\), where \(t\) is the time at which the robot senses an object.

The following predicates describe the state of the robot:

- **At**\((t, loc)\), which is true if, at time \(t\), the robot is in location \(loc\) \((x, y)\) co-ordinates.
- **Battery**\((t, s)\), which is true if, at time \(t\), the robot reports battery status \(s\) (low, high). Here the battery status is set to low when it only has 20% battery and set to high when it has more than 80% battery.
• **Found**(\(t, obj\)), which is true if, at time \(t\), the robot senses object \(obj\).

• **ObjectAt**(\(t, loc, obj\)), which is true if, at time \(t\), object \(obj\) is at location \(loc\).

### 4.1.2 Memory system

We specify a system for the robot to manage its memory so that the robot can represent and update its beliefs, derived from the argumentation elements defined in Section 3 adopted from [Parsons et al., 2003b; Sklar and Parsons, 2004] as follows. Using the ontology described above, this system can store information about the robot’s domain, its physical environment, its ability to interact with the environment, and the human’s capabilities within the domain and environment. This representation supports the robot’s ability to compare and evaluate its choice of actions and includes the following components:

\[
\Sigma_R = \text{robot’s beliefs about itself and its environment} \\
\Gamma_R(H) = \text{robot’s beliefs about the human} \\
CS_R = \text{robot’s commitment store} \\
CS_H = \text{human’s commitment store} \\
\Delta_R = \Sigma_R \cup \Gamma_R(H) \cup CS_R \cup CS_H
\]

The robot’s set of internal beliefs (\(\Sigma_R \cup \Gamma_R(H)\)) is considered *private*, whereas its commitment store, \(CS_R\), contains all its utterances in a dialogue; so we consider the commitment store to be *public*. The robot has access not only to its own commitment store but also to the commitment store of the human with whom it is engaged in a dialogue. Both \(CS_R\) and \(CS_H\) are stored by the robot. This means that the robot can update its beliefs about the human, \(\Gamma_R(H)\), based on \(CS_H\), what the human has said in the dialogue. Indeed, the only way that the robot in our system can update its beliefs about the human’s beliefs is through \(CS_H\). Following the rules of dialogue games, detailed below in Section 4.2, the human can only utter beliefs that s/he can support.
4.1.3  Argumentation engine

A critical component of our system is the application of an argumentation engine that the robot can use to reason about how a goal might be achieved or to resolve conflicts found in the components of its memory.

Conflicts can occur two ways [Sklar and Azhar, 2015] and are detailed in Section 3: (1) undermining–where the human’s conclusion of one argument conflicts with the conclusion of the robot’s arguments or vice versa; and (2) rebuttal–where the conclusion of the human’s argument conflicts with some element in the support of the robot’s argument or vice versa. It is important to note that the robot has a representation that captures what the robot believes about the human’s beliefs, based on what the human says in the dialogue. As illustrated in Figure 3.1, undermining and rebuttal are identified in the argumentation domain as attack relations between arguments.

To resolve a conflict, the robot and the human can engage in an argumentation-based dialogue with each other. The dialogue system is described in the next section. The argumentation engine that we adapt is called ArgTrust and is a partial implementation of the formal system from [Tang et al., 2011a]. A brief outline of ArgTrust is included in Section 5.2.2.

4.1.4  Dialogue system

The final component of our ArgHRI framework is a dialogue system for discussing the robot’s beliefs with the human. Three types of dialogues adopted from the model of human dialogues proposed by Doug Walton and Erik Krabbe [Walton and Krabbe, 1995] and mentioned earlier are relevant here: information-seeking, inquiry, and persuasion.

The Dialogue System supports our argumentation-based dialogue games approach adopted from [Parsons et al., 2004] for human-robot collaboration as described in next Section 4.2.
4.2 Approach: Argumentation-based Dialogue Games

Dialogue games originate from well-founded argumentation-based theory and provide an alternative approach to structuring dialogue, supporting less restrictive conversation policies, and more efficient communication [Black, 2007]. In this thesis, we apply argumentation-based dialogue games as the means to facilitate an exchange of ideas during human-robot collaboration. Our formal dialogue games model is adopted from [McBurney and Parsons, 2002]. The model supports a two-player game between a robot $R$, and a human $H$ and incorporates the following components prescribed by [McBurney and Parsons, 2003, 2009a]:

- **Commencement rules**: a set of rules that defines the pre-conditions or circumstances under which the dialogue can begin. Our commencement rules for a dialogue are described in Section 4.2.1.

- **Locutions**: a set of moves consisting of statements, or *locutions*, uttered by one player and directed toward the other player as listed in Figure Section 4.6.

- **Combination Rules**: each player has a set of “moves” she can make in each dialogical context, and the rules of the games dictate which moves are allowed under which conditions. We follow the rules outlined in [Parsons et al., 2004] and described in Section 4.2.1.

- **Commitments**: a set of rules that defines the circumstances under which each player expresses commitment to a proposition, a public commitment store for each player (i.e., $CS_R$ for robot, $CS_H$ for human), which maintains the set of propositions to which each player is currently committed. In our dialogue game model, a player cannot commit to both $b$ and $\neg b$. The commitment store was added to after every utterance, and that the beliefs ($\Sigma_R$ and $\Gamma_R(H)$) where the elements updated after the termination of each dialogue.

- **Speaker Order**: a set of rules that defines the order in which a speaker may make utterances. In our model, only one speaker may speak at any one time.
Termination Rules: a set of rules that enables a dialogue to reach a termination condition, where either both players agree, by accepting the same proposition, or both players reach a stalemate, by failing to accept the same proposition exhausting all possible moves. The termination rules for all three argumentation-based dialogues are described in Sections 4.2.1 and 4.2.2.

We applied the argumentation-based dialogue game and associated rules to HRI by identifying four different real-world human-robot collaborative scenarios for three types of human-robot dialogues identified by Walton and Krabbe [Walton and Krabbe, 1995]:

- the human could suggest the robot to follow her plan discarding its plan in order to pre-empt possible failure or respond to new discovery: persuasion
- the robot could ask the human for information that the robot does not have and believes that the human has, and vice versa to prevent errors: information-seeking
- the robot discovers information that the human does not know or that contradicts something the human knows. In this case, a robot agent tries to alter the beliefs of a human agent: persuasion
- the robot and human together agree to find an answer to unknown query (e.g., unknown failure) neither of them knows how to recover from: inquiry

Unlike the software agent-agent domain [McBurney and Parsons, 2002], we only model the robot’s beliefs and do not attempt to model the human’s mental state in the human-robot domain. We use $b$ (or $\neg b$) to represent a belief put forth by either the robot $R$ or the human $H$. In our model, $b$ is not a set. We use $\Delta_R$ to represent the robot’s beliefs, including $\Gamma_R(H)$, the robot’s beliefs about the human’s beliefs; however, we do not represent $\Delta_H$, which means that all the computations outlined below are based on components of $\Delta_R$. The abstract notation is summarized in Table 4.1. In the following discussion, $Ag_i$ is the participant who initiates the dialogue and the $Ag_j$ is the
respondent. Note that the $Ag_i$ and the $Ag_j$ could be either the human or the robot. As mentioned before $R$ refers specifically to the robot and $H$ refers to the human.

<table>
<thead>
<tr>
<th>symbol</th>
<th>definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>an agent’s belief, read “agent believes $b$”</td>
</tr>
<tr>
<td>$\neg b$</td>
<td>the counter belief to $b$, read “agent believes not $b$”</td>
</tr>
<tr>
<td>$?b$</td>
<td>the agent may believe either $b$ or $\neg b$, but does not have enough (possibly any) information to determine which</td>
</tr>
<tr>
<td>$\Delta_i$</td>
<td>complete knowledge base of agent $Ag_i$; may be inconsistent; partitioned as: $\Delta_i = \Sigma_i \cup CS_i \cup CS_j \cup \Gamma_i(j)$</td>
</tr>
<tr>
<td>$\Sigma_i$</td>
<td>belief set of agent $Ag_i$; must be consistent; we model consistency within a set of beliefs as containing only one of $b$ or $\neg b$ or $?b$</td>
</tr>
<tr>
<td>$CS_i$</td>
<td>commitment store of agent $Ag_i$; may be inconsistent; i.e., everything that agent $Ag_i$ has said, similar to a chat log</td>
</tr>
<tr>
<td>$CS_j$</td>
<td>commitment store of agent $Ag_j$; may be inconsistent; (contains only utterances of $Ag_j$ in dialogue with $Ag_i$)</td>
</tr>
<tr>
<td>$\Gamma_i(j)$</td>
<td>agent $Ag_i$’s beliefs about agent $Ag_j$’s beliefs; i.e., what $Ag_i$ believes that $Ag_j$ believes</td>
</tr>
</tbody>
</table>

Table 4.1: Our notation: types of knowledge, or partitions, of agent’s belief set

We consider the agent’s mental state before a dialogue begins as consisting of a set of “pre-conditions,” according to the agent’s current beliefs. As in Table 4.1, an agent may either believe $b$, believe $\neg b$, or hold inconclusive (or no) information about $b$.  So if the robot believes $b$, then we write $b \in \Sigma_R$. If the robot believes $\neg b$, then we write $\neg b \in \Sigma_R$. If the robot has no information about $b$, then we write $?b \in \Sigma_R$, which is equivalent to $b \not\in \Sigma_R \land \neg b \not\in \Sigma_R$ incorporating syntax from [Cogan et al., 2005]. Note that we cannot have $b \in \Sigma_R \land \neg b \in \Sigma_R$, i.e., conflicting information about $b$ held simultaneously in $\Sigma_R$, because that goes against the rule that requires $\Sigma_R$ to be consistent (see definition of $\Sigma_i$ in Table 4.1).

Table 4.2 illustrates all possible combinations of pre-conditions for the robot’s views about $b$ and the different types of dialogue between the robot and the human collaborator. The columns hold the information about the robot’s beliefs as contained in $\Sigma_R$. The rows hold the robot’s beliefs

---

1This treatment of uncertainty with respect to $b$ is taken from Dempster-Shafer Theory [Shafer, 1976], which distinguishes between “belief,” “disbelief,” and “uncertainty.”
about the human collaborator’s beliefs $\Gamma_R(H)$.

<table>
<thead>
<tr>
<th></th>
<th>$b \in \Sigma_R$</th>
<th>$\neg b \in \Sigma_R$</th>
<th>$?b \in \Sigma_R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b \in \Gamma_R(H)$</td>
<td>agreement</td>
<td>persuasion</td>
<td>information-seeking</td>
</tr>
<tr>
<td>$\neg b \in \Gamma_R(H)$</td>
<td>persuasion</td>
<td>agreement</td>
<td>information-seeking</td>
</tr>
<tr>
<td>$?b \in \Gamma_R(H)$</td>
<td>information-seeking</td>
<td>information-seeking</td>
<td>inquiry</td>
</tr>
</tbody>
</table>

Table 4.2: Pre-conditions: robot’s views about $b$ prior to dialogue

We further identify the reasons for each pre-condition as one of the following four situations:

- **agreement** due to no conflict with beliefs;
- **disagreement** due to conflict with beliefs;
- **lack of knowledge** due to no knowledge about a belief by either the robot or the human collaborator. Thus agreement or disagreement is not yet possible; and
- **shared lack of knowledge** due to no knowledge about a belief by either the robot or the human collaborator.

Each situation is discussed below. These boil down to four dialogue cases:

<table>
<thead>
<tr>
<th></th>
<th>$b \in \Delta_R$</th>
<th>$\neg b \in \Delta_R$</th>
<th>$?b \in \Delta_R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b \in \Gamma_R(H)$</td>
<td>case 1</td>
<td>case 2</td>
<td>case 3</td>
</tr>
<tr>
<td></td>
<td>agreement</td>
<td>disagreement</td>
<td>lack of knowledge</td>
</tr>
<tr>
<td></td>
<td>(no dialogue)</td>
<td></td>
<td>information-seeking</td>
</tr>
<tr>
<td>$\neg b \in \Gamma_R(H)$</td>
<td>case 4</td>
<td>case 5</td>
<td>case 6</td>
</tr>
<tr>
<td></td>
<td>disagreement</td>
<td>agreement</td>
<td>lack of knowledge</td>
</tr>
<tr>
<td></td>
<td>persuasion</td>
<td>(no dialogue)</td>
<td>information-seeking</td>
</tr>
<tr>
<td>$?b \in \Gamma_R(H)$</td>
<td>case 7</td>
<td>case 8</td>
<td>case 9</td>
</tr>
<tr>
<td></td>
<td>lack of knowledge</td>
<td>lack of knowledge</td>
<td>shared lack of knowledge</td>
</tr>
<tr>
<td></td>
<td>information-seeking</td>
<td>information-seeking</td>
<td>inquiry</td>
</tr>
</tbody>
</table>

Table 4.3: Cases for different types of dialogues
• Agreement (cases 1 and 5 in Table 4.3).

The robot believes $b$ and the human believes $b$, or the robot believes $\neg b$ and the human believes $\neg b$. They are represented formally as:

$$b \in \Delta_R \land b \in \Gamma_R(H)$$

or

$$\neg b \in \Delta_R \land \neg b \in \Gamma_R(H)$$

respectively. These are cases where the robot and the human agree about $b$ or $\neg b$, and so no dialogue is necessary.

• Disagreement (cases 2 and 4 in Table 4.3).

The robot believes $\neg b$ and the human believes $b$, or the robot believes $b$ and the human believes $\neg b$, represented formally as:

$$\neg b \in \Delta_R \land b \in \Gamma_R(H)$$

or

$$b \in \Delta_R \land \neg b \in \Gamma_R(H)$$

respectively. These are cases of disagreement and warrant a persuasion dialogue where either the robot initiates a dialogue to convince the human to change her belief to $b$ or $\neg b$ or the human initiates a dialogue to convince the robot to change its belief to $b$ or $\neg b$. For example, in an object-identification task, the robot believes there is no red box in an image, and the human believes there is a red box in the image.

• Lack of Knowledge (cases 3, 6, 7 and 8 in Table 4.3).

The robot has no knowledge about $b$ or $\neg b$, and the human believes $b$ or $\neg b$, or the human
has no knowledge about $b$ or $\neg b$, and the robot believes $b$ or $\neg b$, represented formally as:

$$ \neg ?b \in \Delta_R \land (b \in \Gamma_R(H) \lor \neg b \in \Gamma_R(H)) $$

or

$$ \neg ?b \in \Gamma_R(H) \land (b \in \Delta_R \lor \neg b \in \Delta_R) $$

This is a case of lack of knowledge on the part of the robot or the human and warrants an information-seeking dialogue to be initiated by the party that is lacking knowledge. For example, in an object-identification task, the robot does not have any information about what is in a particular image, and the human believes there is a red box in the image.

- **Shared Lack of Knowledge** (case 9 in Table 4.3).

  The robot has no knowledge about $b$, nor does the human have any knowledge about $b$, represented formally as:

  $$ \neg ?b \in \Delta_R \land \neg ?b \in \Gamma_R(H) $$

  This is a case of shared lack of knowledge and warrants an inquiry dialogue to be initiated by either the robot or the human. For example, in a sensor-sweep task, neither the robot nor the human have any information about whether there are any treasures in room 1.

Here we identified reasons in which information-seeking, inquiry, or persuasion dialogue can be used for exchanging information for collaborative decisions. The next section (4.2.1) includes protocols for the argumentation-based dialogues and axiomatic semantics for each type of utterance described in the dialogue protocols.

### 4.2.1 Dialogue Protocols

In this section, for each type of dialogue, we discuss the following dialogue protocols:
• the *opening move* enables a particular dialogue to start. The opening move is the required utterance or locution that is employed at the start of an individual dialogue by either the robot or human collaborator \((\text{Ag}_i)\) who initiates the dialogue.

• *possible moves* are the set of possible utterances or locutions that can be invoked in response to the first utterances, and so forth. For example, the *challenge moves* are *possible moves* that enable participants to challenge each other. These are the set of possible utterances or locutions that can be invoked to challenge or are in response to the challenge utterances.

• *termination moves* enable a dialogue to terminate. These are the set of possible utterances that a robot or the human collaborator employs at the end of a dialogue to accept or reject an argument. The *reject* move allows an agent to reject a belief (conclusion) explicitly, if there is insufficient evidence to support that belief. We consider the following reasons for rejection: an agent fails to provide convincing support for a challenge or an agent does not believe or agree with the evidence contained in the support.

We represent the dialogue protocol incorporating the basic model of a deterministic finite automaton (DFA), based on protocols from [Parsons et al., 1998, 2003b; Fernández and Endriss, 2007], since it allows the start or end of a dialogue and possible follow up at a given point in a dialogue to be formalized. These are illustrated graphically in Figures 4.1, 4.2, and 4.3. In the following discussion, the *participant goals* describe overlapping goals of both participants that motivates a particular type of *dialogue* and the *dialogue goals* determine the overall behavior of a dialogue [Levin and Moore, 1977; Walton and Krabbe, 1995].

**Persuasion Dialogue**

The persuasion dialogue [Prakken, 2006] provides opportunities for either the robot or the human to convince each other of the truth of a proposition. The persuasion dialogue protocol is illustrated graphically using a DFA in Figure 4.1.
• Initial Conditions or Pre-Conditions: Participants have conflicting points of view or disagree, as described in Table 4.4. For example, if the robot believes $b$ (i.e., $b \in \Delta_R$) but it believes that the human believes $\neg b$ (i.e., $\neg b \in \Gamma_R(H)$), then the robot will engage in a persuasion dialogue with the human collaborator.

<table>
<thead>
<tr>
<th>$b \in \Gamma_R(H)$</th>
<th>$b \in \Delta_R$</th>
<th>$\neg b \in \Delta_R$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>case 1</strong></td>
<td>agreement (no dialogue)</td>
<td>disagreement persuasion</td>
</tr>
<tr>
<td>$\neg b \in \Gamma_R(H)$</td>
<td>disagreement persuasion</td>
<td><strong>case 5</strong> agreement (no dialogue)</td>
</tr>
</tbody>
</table>

Table 4.4: pre-conditions: persuasion dialogue

• Participant goals: Each participant intends to persuade the other.

• Dialogue goal: The goal of the persuasion dialogue is to resolve the conflict via arguments. For example, if the robot can successfully persuade the human about its proposition $b$ ($b \in \Delta_R$) after the successful completion of the persuasion dialogue, the robot’s belief about the human’s belief will be updated from $\neg b \in \Gamma_R(H)$ to $b \in \Gamma_R(H)$.

<table>
<thead>
<tr>
<th>current move or location</th>
<th>possible moves or locations</th>
<th>comments</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>assert(b)</code></td>
<td><code>accept(b)</code></td>
<td>$A_{g_j}$ simply responds to $A_{g_i}$ accepting $b$ that will terminate the dialogue when $b \in \Delta_{A_{g_i}}$</td>
</tr>
<tr>
<td><code>assert(b)</code></td>
<td><code>assert(\neg b)</code></td>
<td>$A_{g_j}$ attacks $A_{g_i}$ with counter assertion when $\neg b \in \Delta_{A_{g_i}}$</td>
</tr>
<tr>
<td><code>assert(b)</code></td>
<td><code>challenge(b)</code></td>
<td>$A_{g_j}$ challenges $A_{g_i}$’s assertion that requires $A_{g_i}$ to justify its assertion when ($b \notin \Delta_{A_{g_i}} \land \neg b \notin \Delta_{A_{g_i}}$)</td>
</tr>
</tbody>
</table>

Table 4.5: `assert(b)` location and possible moves during persuasion dialogue

• Protocols:
  - A persuasion dialogue can be opened by participant $A_{g_i}$ uttering `assert(b)` to $A_{g_j}$ and thereby satisfying the pre-conditions of the dialogue game described formally in Table 4.2.
– $Ag_j$ may respond to the $assert(b)$ move by uttering the possible locutions described in Table 4.5:
– $Ag_i$ can defend $Ag_j$’s challenge move by providing a supporting argument using $assert(s \in S)$ where $(S, b)$. $Ag_j$ must accept every element in $S$ for $(S, b)$ to be accepted and hence for $b$ to be accepted. It is an iterative process where $Ag_i$ cycles through and asserts each $s \in S$.
– $Ag_j$ can also challenge $Ag_i$’s initial move $assert(b)$ by uttering $assert(\neg b)$, which will cause a conflict with $Ag_i$’s assertion $b$. In that case, $Ag_i$ can challenge $Ag_j$, which will trigger the same iterative challenge process (as above) where $Ag_i$ is playing the role of challenger and $Ag_j$ is playing the role of defender. Similarly, $Ag_i$ must accept every element in $S$ for $(S, \neg b)$ to be accepted and hence for $\neg b$ to be accepted.
– Participants can terminate the dialogue by uttering accept and by agreeing with $b$ or $\neg b$ or supporting the argument $(S, b)$. Participants can also terminate the dialogue by uttering the reject locution and disagreeing with $b$ or $\neg b$ or any of the supporting argument(s) $(S, b)$.

**Inquiry Dialogue**

The inquiry dialogue [McBurney and Parsons, 2001] provides opportunities for both the robot and the human to collaborate in finding an answer to a question to which neither knows the answer. The inquiry dialogue is illustrated graphically using the DFA protocol in Figure 4.2.

- Initial Conditions or Pre-Conditions: Both participants are ignorant about some topic or do not know the answer to a question, described formally in Table 4.6. For example, if the robot does not know about $b$ (i.e., $b \not\in \Delta_R \land \neg b \not\in \Delta_R$ or $?b \in \Delta_R$) and it has become aware from a previous discussion that the human does not know either (i.e., $b \not\in \Gamma_R(H) \land \neg b \not\in \Gamma_R(H)$ or $?b \in \Gamma_R(H)$), then the robot will engage in an inquiry dialogue with the human collaborator.
persuasion dialogue protocol:

\[
\begin{array}{c}
S: \text{assert}(b) \quad \text{accept}(b) \\
\text{assert}(s \in S) \quad \text{where } (S, b) \\
\text{accept}(s) \quad \text{reject}(b) \\
\text{challenge}(b) \quad \text{assert}(b) \\
\text{challenge}(b) \quad \text{assert}(b) \\
\text{accept}(\neg b) \\
\text{accept}(s)
\end{array}
\]

Figure 4.1: Persuasion Dialogue protocol, drawn as a state machine. The start state is indicated with an \(\text{S}\). Termination states are indicated with double circles. States shown without fill are states in which the initiating agent is expected to make a move in the dialogue game; states filled in grey are states in which the responding agent is expected to make a move [Sklar and Azhar, 2015].

\[b \in \Delta_R\]

\[b \in \Gamma_R(H)\]

<table>
<thead>
<tr>
<th>(b \in \Delta_R)</th>
<th>(b \in \Gamma_R(H))</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 9</td>
<td>shared lack of knowledge inquiry</td>
</tr>
</tbody>
</table>

Table 4.6: pre-conditions: inquiry dialogue

- Participant goals: Both participants intend to find an answer to a question.

- Dialogue goal: The goal of the inquiry dialogue is to increase shared knowledge. After the successful completion of an inquiry dialogue, both the robot and the human will have acquired information about a belief, which could either be to believe \(b\) or \(\neg b\).

- Protocols:
  - An inquiry dialogue can be opened by participant \(Ag_i\) uttering \(\text{propose}(a \rightarrow b)\) to \(Ag_j\) satisfying pre-conditions of the dialogue games described in Table 4.2. We introduce the \(\text{propose}\) utterance to distinguish it from the use of \(\text{assert}\) for persuasion, although Parsons et al. [2003b] use the \(\text{assert}\) utterance in an inquiry dialogue. We also assume
that the agents are already aware of the existence of \( b \) and the evidence (i.e., \( a \)) that may imply \( b \) is either true or false. Therefore, the opening move in the inquiry dialogue is a proposal by the initiator (i.e., \( Ag_i \)) that the proposition \( a \) implies \( b \) [Sklar and Azhar, 2015].

- \( Ag_j \) may respond to the \( propose(a \rightarrow b) \) move by uttering the following possible locutions described in Table 4.7:

- \( Ag_j \) can challenge \( Ag_i \)’s move \( propose(a \rightarrow b) \) by uttering \( challenge(a \rightarrow b) \). \( Ag_i \) can defend \( Ag_j \)’s challenge move by providing a supporting argument using \( propose(s \in S) \) where \( (S,b) \). \( Ag_j \) must accepts every element in \( S \) for \( (s \in S, b) \) or \( (s \in S, \neg b) \) to be accepted and hence for \( b \) to be accepted. It is an iterative process where \( Ag_j \) cycles and asserts each \( s \in S \).

- \( Ag_j \) can terminate the dialogue by uttering \( accept \) and agreeing with \( a \rightarrow b \) or all the supporting argument(s) \( (S, a \rightarrow b) \) for \( a \rightarrow b \). \( Ag_j \) can also terminate the dialogue by uttering the \( reject \) locution and disagreeing with \( a \rightarrow b \) or any of the supporting argument(s) \( (S, a \rightarrow b) \) for \( a \rightarrow b \).

<table>
<thead>
<tr>
<th>current move or locution</th>
<th>possible moves or locations</th>
<th>comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>( propose(a \rightarrow b) )</td>
<td>( accept(b) )</td>
<td>( Ag_j ) simply responds to ( Ag_j ) accepting the proposal ( a \rightarrow b ) when ( b \in \Delta_{Ag_j} ) or ( a \rightarrow b \in \Delta_{Ag_j} )</td>
</tr>
<tr>
<td>( propose(a \rightarrow b) )</td>
<td>( challenge(a \rightarrow b) )</td>
<td>( Ag_j ) challenges ( Ag_i )’s proposition ( a \rightarrow b ) when ( \neg b \in \Delta_{Ag_j} ) or ( ?b \in \Delta_{Ag_j} ) or ( b \notin \Delta_{Ag_j} )</td>
</tr>
</tbody>
</table>
(c) *inquiry* dialogue protocol:

![Diagram of Inquiry Dialogue Protocol]

Figure 4.2: Inquiry Dialogue protocols, drawn as a state machine. The start state is indicated with an (S). Termination states are indicated with double circles. States shown without fill are states in which the initiating agent is expected to make a move in the dialogue game; states filled in grey are states in which the responding agent is expected to make a move [Sklar and Azhar, 2015].
Information-Seeking Dialogue

An information-seeking dialogue [Walton and Krabbe, 1995] provides opportunities for both the robot and the human to get information from one another. An Information-seeking dialogue is illustrated graphically in Figure 4.3 using a DFA.

- Initial Conditions or Pre-Conditions: One participant is ignorant on a topic and believes that the other participant knows the information \( b \), described formally in Table 4.8. For example, if the robot does not know about \( b \) (i.e., \( b \not\in \Delta_R \land \neg b \not\in \Delta_R \) or \( ?b \in \Delta_R \)) but believes that the human does (i.e., \( b \in \Gamma_R(H) \land \neg b \in \Gamma_R(H) \)), then the robot will engage in an information-seeking dialogue with the human collaborator.

<table>
<thead>
<tr>
<th>( b \in \Gamma_R(H) )</th>
<th>( b \in \Delta_R )</th>
<th>( \neg b \in \Delta_R )</th>
<th>( ?b \in \Delta_R )</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 1</td>
<td>agreement (no dialogue)</td>
<td>case 2</td>
<td>disagreement persuasion</td>
</tr>
<tr>
<td>case 3</td>
<td>lack of knowledge</td>
<td>information-seeking</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( \neg b \in \Gamma_R(H) )</th>
<th>( b \in \Delta_R )</th>
<th>( \neg b \in \Delta_R )</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 4</td>
<td>disagreement persuasion</td>
<td>case 5</td>
</tr>
<tr>
<td>case 6</td>
<td>lack of knowledge</td>
<td>information-seeking</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( ?b \in \Gamma_R(H) )</th>
<th>( b \in \Delta_R )</th>
<th>( \neg b \in \Delta_R )</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 7</td>
<td>lack of knowledge</td>
<td>case 8</td>
</tr>
<tr>
<td>case 9</td>
<td>information-seeking</td>
<td>information-seeking</td>
</tr>
</tbody>
</table>

Table 4.8: pre-conditions: information-seeking dialogue

- Participant goals: One participant intends to find the answer to the question.

- Dialogue goal: The goal of the information-seeking dialogue is to share knowledge. After successful completion of an information-seeking dialogue, the initiator \( Ag_i \) will have acquired information about a belief, which could be either \( b \) or \( \neg b \).

- Protocols:
  - An information-seeking dialogue can be opened by participant \( Ag_i \) uttering question(\( b \)) to \( Ag_j \) which in turn satisfies the pre-conditions of the dialogue game as described in
Table 4.2.

- $Ag_j$ may respond to question($b$) move by uttering the following possible locations described in Table 4.9:

<table>
<thead>
<tr>
<th>current move or location</th>
<th>possible moves or locations</th>
<th>comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>question($b$)</td>
<td>assert($b$)</td>
<td>$Ag_j$ simply responds to $Ag_i$ with an answer $b$ when $b \in \Delta_{Ag_j}$</td>
</tr>
<tr>
<td>question($b$)</td>
<td>assert($\neg b$)</td>
<td>$Ag_j$ responds to $Ag_i$ with an answer $\neg b$</td>
</tr>
<tr>
<td>question($b$)</td>
<td>assert($U$)</td>
<td>$Ag_j$ responds to $Ag_i$ with an answer $U$ or &quot;don't know&quot; because it does not have any knowledge of $b$ when $?b \in \Delta_{Ag_j}$</td>
</tr>
</tbody>
</table>

Table 4.9: question($b$) location and possible moves during information-seeking dialogue

- $Ag_i$ can challenge $Ag_j$’s assert($b$) move by uttering the challenge($b$). $Ag_j$ can defend $Ag_i$’s challenge move by providing a supporting argument using assert($s \in S$) where $(S, b)$. $Ag_i$ must accept every element in $S$ for $(S, b)$ to be accepted and hence for $b$ to be accepted. It is an iterative process where $Ag_j$ cycles through each $s \in S$.

$Ag_i$ can also challenge $Ag_j$’s assert($\neg b$) move by uttering challenge($\neg b$). In that case, $Ag_i$ can challenge $Ag_j$, which will trigger the same iterative challenge process (as above) where $Ag_i$ is playing the role of challenger and $Ag_j$ is playing the role of defender. Similarly, $Ag_i$ must accept every element in $S$ for $(S, \neg b)$ to be accepted and hence for $\neg b$ to be accepted.

- As mentioned, $Ag_j$ can terminate the dialogue immediately by uttering assert($U$) followed by $Ag_j$’s question($b$) when $Ag_j$ has no knowledge of $b$. $Ag_i$ can terminate dialogue by uttering accept and in turn by agreeing with $b$ or $\neg b$ or supporting the argument(s) $(S, b)$ for $b$. $Ag_i$ can also terminate dialogue by uttering reject locution and in turn by disagreeing with $b$ or $\neg b$ or supporting argument(s) $(S, b)$ for $b$.

Examples of possible information-seeking dialogues are presented below based on Figure 4.3. In these examples, the robot and human are collaboratively searching for red boxes in the robot’s
environment. The robot explores the environment and takes pictures and then sends the pictures to the human for analysis. The robot may do some cursory filtering of an image, but relies on the human for comprehensive image processing. We represent the belief that there is a red box in the image as $b$ and the belief that there is not a red box in the image as $\neg b$. The robot starts in an initial state, which can be represented in terms of pre-conditions based on the robot’s knowledge store.

In Example1, (See Figure 4.4), the robot ($R$) asks a question by uttering $question(H,R,b)$; the human ($H$) responds with an answer by uttering $assert(R,H,b)$; and the robot accepts the answer by uttering $accept(H,R,b)$. In Example2, (See Figure 4.5), the robot ($R$) asks a question; the human ($H$) responds with an answer ($\neg b$); and the robot challenges the answer ($\neg b$).
Figure 4.4: Example 1

<table>
<thead>
<tr>
<th>Pre-conditions:</th>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>?b ∈ Σ_R</td>
<td>the robot does not know if there is a red box in the image</td>
<td></td>
</tr>
<tr>
<td>(b ∧ ¬b) ∈ Γ_R(H)</td>
<td>the robot believes that the human knows whether there is a red box in the image or not</td>
<td></td>
</tr>
</tbody>
</table>

Dialogue sequence: In this example, the robot initiates an information-seeking dialogue.

<table>
<thead>
<tr>
<th>current location</th>
<th>dialogue move</th>
<th>next location</th>
</tr>
</thead>
<tbody>
<tr>
<td>question from R to H</td>
<td>question(H, R, b)</td>
<td>assert from H to R</td>
</tr>
<tr>
<td>assert from H or R</td>
<td>assert(R, H, b)</td>
<td>challenge or accept or reject from R to H</td>
</tr>
<tr>
<td>accept from R to H</td>
<td>accept(H, R, b)</td>
<td>Great! We found the red box.</td>
</tr>
<tr>
<td></td>
<td>dialogue terminates</td>
<td>update belief(s)</td>
</tr>
</tbody>
</table>

Post-conditions:

<table>
<thead>
<tr>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>b ∈ Σ_R</td>
<td>robot believes that there is a red box in the image.</td>
</tr>
<tr>
<td>b ∈ Γ_R(H)</td>
<td>robot believes that the human believes that there is a red box in the image.</td>
</tr>
</tbody>
</table>

Figure 4.5: Example 2

<table>
<thead>
<tr>
<th>Pre-conditions:</th>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>?b ∈ Σ_R</td>
<td>the robot does not know if there is a red box in the image</td>
<td></td>
</tr>
<tr>
<td>b ∨ ¬b ∈ Γ_R(H)</td>
<td>the robot believes that the human knows whether there is a red box in the image or not</td>
<td></td>
</tr>
</tbody>
</table>

Dialogue sequence:

<table>
<thead>
<tr>
<th>current location</th>
<th>dialogue move</th>
<th>next location</th>
</tr>
</thead>
<tbody>
<tr>
<td>question from R to H</td>
<td>question(H, R, b)</td>
<td>assert from H to R</td>
</tr>
<tr>
<td>assert from H to R</td>
<td>assert(R, H, ¬b)</td>
<td>challenge or accept or reject from R to H</td>
</tr>
<tr>
<td>challenge from R to H</td>
<td>challenge(H, R, ¬b)</td>
<td>accept or reject from R to H</td>
</tr>
<tr>
<td>assert from H to R</td>
<td>assert(R, H, S(¬b))</td>
<td>accept or reject from R to H</td>
</tr>
<tr>
<td>accept from R to H</td>
<td>accept(H, R, ¬b)</td>
<td>Ok, there is no red box in the image.</td>
</tr>
<tr>
<td></td>
<td>dialogue terminates</td>
<td>update belief(s)</td>
</tr>
</tbody>
</table>

Post-conditions:

<table>
<thead>
<tr>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>¬b ∈ Σ_R</td>
<td>robot believes that there is no red box in the image.</td>
</tr>
<tr>
<td>¬b ∈ Γ_R(H)</td>
<td>robot believes that human believes that there is no red box in the image.</td>
</tr>
</tbody>
</table>
4.2.2 Axiomatic Semantics

We will now discuss axiomatic semantics [McBurney and Parsons, 2009b], which, following the protocol rules [McBurney and Parsons, 2005], specify how the states of the system change as a result of the execution of the locutions in an argumentation dialogue. Axiomatic semantics provide the rules for deciding which utterance(s) can be invoked by each participant at distinct points during the interchange. They enable us to view dialogue locutions as state transition operators making an explicit connection between the mental states of the participants and public states of dialogue. In addition, axiomatic semantics show how these relationships change as a result of utterances or dialogue moves and internal agent decisions [McBurney and Parsons, 2002]. We defined six different utterances or locutions in the dialogue protocols in Section 4.2.1 for three types of dialogue: persuasion, information-seeking and inquiry. The utterances are: accept, assert, challenge, propose, question, and reject.

In addition to the rules detailed in the dialogue protocols about which locutions can be uttered in sequence, there are rules that dictate restrictions on the utterances themselves. For example, for an agent to be allowed to utter \texttt{assert}(b), then \textit{b} must be in the agent’s knowledge base or in the commitment store of one of the agents engaged in the dialogue. The \textit{pre-conditions} for each type of move are listed in Figure 4.6. After a locution is uttered in the dialogue, rules are invoked that outline how the different components of the agent’s memory are updated. These can be referred to as \textit{post-conditions} and are illustrated in Figure 4.6.
<table>
<thead>
<tr>
<th><strong>Locution:</strong></th>
<th><strong>Pre-conditions:</strong></th>
<th><strong>Post-conditions:</strong></th>
</tr>
</thead>
</table>
| `assert(b)`    | 1. $b \in Ag_i.\Sigma$  
2. $(S, b) \in \mathcal{A}(Ag_i.\Sigma)$  
3. $b \not\in Ag_i.\Gamma(j)$ | 1. $Ag_i.CS \leftarrow assert(b)$ |
| `assert(S, b)` | 1. $b \in Ag_i.\Sigma$  
2. $(S, b) \in \mathcal{A}(Ag_i.\Sigma)$  
3. $b \not\in Ag_i.\Gamma(j)$ | 1. $Ag_i.CS \leftarrow assert(S, b)$ |
| `assert(U)`    | (terminates dialogue)  
1. $?b \in Ag_i.\Sigma$ | 1. $Ag_i.CS \leftarrow assert(U)$  
2. $Ag_i.\Sigma$ : no change |
| `challenge(b)` | 1. $b \in Ag_j.CS$  
2. $b \not\in Ag_i.\Sigma$  
3. $(S, b) \in Ag_i.\Gamma(j)$ | 1. $Ag_i.CS \leftarrow challenge(b)$ |
| `propose(a \rightarrow b)` | 1. $a \in Ag_i.\Sigma$  
2. $b \not\in Ag_i.\Sigma$  
3. $b \not\in Ag_i.\Gamma(j)$ | 1. $Ag_i.CS \leftarrow propose(a \rightarrow b)$ |
| `question(b)`  | (terminates dialogue)  
1. $?b \in Ag_i.\Sigma$  
2. $b \in Ag_i.\Gamma(j)$ | 1. $Ag_i.CS \leftarrow question(b)$ |
| `accept(b)*`   | (terminates dialogue)  
1. $b \not\in Ag_i.\Sigma$  
2. $b \in Ag_j.CS$  
3. $b \in Ag_i.\Gamma(j)$  
4. $(S, b) \in \mathcal{A}(Ag_i.\Gamma(j))$ | 1. $Ag_i.CS \leftarrow accept(b)$  
2. $Ag_i.\Sigma \leftarrow \{b\}$  
3. $\mathcal{A}(Ag_i.\Sigma) \leftarrow \{(S, b)\}$  
4. $Ag_i.\Gamma(j)$ : no change |
| `reject(b)*`   | (terminates dialogue)  
1. $b \not\in Ag_i.\Sigma$  
2. $(S, b) \not\in \mathcal{A}(Ag_i.\Sigma)$  
3. $b \in Ag_j.CS$ | 1. $Ag_i.CS \leftarrow reject(b)$  
2. $Ag_i.\Sigma$ : no change  
3. $Ag_i.\Gamma(j)$ : no change |

Figure 4.6: Axiomatic Semantics.
Table 4.10: Opening moves

<table>
<thead>
<tr>
<th>dialogue type</th>
<th>opening move</th>
</tr>
</thead>
<tbody>
<tr>
<td>persuasion</td>
<td>assert(b)</td>
</tr>
<tr>
<td>inquiry</td>
<td>propose(a → b)</td>
</tr>
<tr>
<td>information-seeking</td>
<td>question(b)</td>
</tr>
</tbody>
</table>

The opening move in a dialogue indicates which type of dialogue is underway. For example, an information-seeking dialogue requires a question move as its opening move. Table 4.10 summarizes the dialogue moves that may be uttered to open persuasion, inquiry, or information-seeking dialogues when pre-conditions for each dialogue are satisfied. Two of the locutions can be used only in the middle of a dialogue: the challenge(b) move can be uttered when one participant wants to attack the other participants proposed argument. An assert(s) move allows a defender to provide supporting evidence to the attacker. Only the commitment store (CS) of the speaking agent is updated after the intermediate locutions are presented—with the locution that is uttered.

The rules described in the dialogue protocols in Section 4.2.1 for each type of dialogue define the allowable set of responses for each opening and subsequent move. All three dialogues usually terminate when one of two locutions is uttered: accept or reject. The post-conditions for these locutions require updating the robot’s own beliefs (ΣR) and robot’s beliefs about the human’s beliefs, ΓR(H). It is important to note that Agj can also utter assert(U) immediately after the Agj’s question(b) move to terminate an information-seeking dialogue when Agj has no knowledge about the question just asked. This will update both the agents’ beliefs about b to ?b. In this case, the next possible dialogue about b will be an inquiry dialogue due to a shared lack of knowledge.

4.2.3 Control Layer

We incorporate the idea of a control layer [McBurney and Parsons, 2002] to implement the formal dialogue game described above. A control layer provides the means to start (commencement) or end (termination) a specific dialogue type and the transition between these types. The control layer
supports three types of dialogues we consider (i.e., persuasion, inquiry, and information-seeking) as *Atomic Dialogue Types*. We incorporate the following control layer locutions from [McBurney and Parsons, 2002] where \(G(p)\) is an instance of a \(G\)-type dialogue regarding topic \(p\):

- **BEGIN\((G(p))\)**, to start a dialogue of type \(G\) about topic \(p\)
- **END\((G(p))\)**, to end a dialogue of type \(G\) about topic \(p\)
- **AGREE\((G(p))\)**, to agree to start the dialogue \(G(p)\) (in response to BEGIN)
- **DISAGREE\((G(p))\)**, to disagree to start the dialogue \(G(p)\) (in response to BEGIN)
- **PROPOSE\(_{\text{RETURN\_CONTROL}}\)**, to return the dialogue to the control layer, which will allow a party to start a new dialogue (after END)
- **AGREE\(_{\text{RETURN\_CONTROL}}\)**, to agree to return to the control layer (after PROPOSE\(_{\text{RETURN\_CONTROL}}\))
- **END\(_{\text{CONTROL}}\)**, to terminate the control layer

A robot and the human collaborator need to have capabilities to engage in *sequential*, *embedded*, or *parallel* dialogues to make decisions and perform missions together. The control layers allow multiple dialogues to occur in parallel and keep track of which dialogue(s) are active at any given time. Figure 4.7 illustrates the use of control layers for three types of dialogue combinations:

- **sequential** dialogues, where one dialogue ends before another dialogue begins. For example, a robot may start an inquiry dialogue with its human collaborator after the human has uttered *assert\((U)\)*, sharing his/her lack of knowledge, to terminate an information-seeking dialogue initiated by the robot. In this case, the information-seeking dialogue will terminate first and update both the robot’s belief and the robot’s belief about the human’s belief from \(b\) to \(?b\). This will satisfy the pre-conditions for either the human or the robot to start an inquiry dialogue.
• *embedded* dialogues, where a new dialogue starts and ends before another, current dialogue terminates. For example, a robot may engage in an inquiry dialogue with a human to decide on (a) what kinds of sensor data to collect and (b) from which locations. The human collaborator may disagree with the robot about the location but agree with what kind of sensor data needs to be collected. In this case, the human will embed a persuasion dialogue before the robot terminates its inquiry dialogue. The robot’s belief and robot’s belief about the human’s belief will be updated after termination of all parallel dialogues [Parsons and Sklar, 2006].

• *parallel* dialogues, where a new dialogue starts after another current dialogue, but terminates after the current dialogue, and locutions from each dialogue may be interleaved. A robot may engage in multiple parallel dialogues where one dialogue does not depend on the other dialogue. For example, in parallel, the robot may engage with a human in two different inquiry dialogues to decide on (a) what kinds of sensor data to collect and (b) from which locations. The human collaborator may disagree with the robot about the location but agree with what kind of sensor data needs to be collected. In this case, the human will embed a persuasion dialogue before the robot terminates its inquiry dialogue. The robot’s belief and robot’s belief about the human’s belief will be updated after termination of all embedded dialogues [Parsons and Sklar, 2006].

The next sequence of examples illustrates the use of each type of dialogue combination, facilitated through a control layer (CL). The context and notation is the same as in Section 4.2.1. Note that some information (*next state* column, pre and post conditions) is left out for brevity.
Figure 4.7: Control layers for different combinations of dialogues. A diamond-shaped node labeled CL represents the control layer. A round node labeled d.s1 represents the beginning state of a dialogue, and d.f represents the end state of the dialogue. The * between the d.s1 and d.f nodes indicate a variable number of internal states for each dialogue. When multiple dialogues occur concurrently, as in (b) and (c), the states of the different dialogues are distinguished by the prefixes d1 and d2, instead of d.
### Example 3: Sequential dialogue

<table>
<thead>
<tr>
<th>current state</th>
<th>dialogue move</th>
</tr>
</thead>
<tbody>
<tr>
<td>CL</td>
<td>BEGIN(H,R,question(b))</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,question(b))</td>
</tr>
</tbody>
</table>

**d1**: s1  
question(H,R,b)  
Is it a red box?

| d1: s2 | assert(R,H,b) | Yes, it’s a red box. |
| d1: s3 | accept(H,R,b) | Great! We found the red box. |

| d1: f1 | END(INFO-SEEK(b)) | terminate dialogue d1 |

| CL | PROPOSE-RETURN-CONTROL(R,H) |
| CL | AGREE(H,R,RETURN_CONTROL) |
| CL | BEGIN(R,H,question(c)) | Can I ask you another question? |
| CL | AGREE(H,R,question(c)) | Yes, Sure. |

| d2: s1 | question(R,H,c) | Did you find four boxes? |
| d2: s2 | assert(H,R,¬c) | No, I did not find four boxes. |
| d2: s3’ | accept(R,H,¬c) | Got it. You did not find four boxes. |

| d2: f1’ | END(INFO-SEEK(c)) | terminate dialogue d2 |

| CL | END(CONTROL) | terminate all dialogues |
### Example 4: Embedded dialogue

<table>
<thead>
<tr>
<th>current state</th>
<th>dialogue move</th>
</tr>
</thead>
<tbody>
<tr>
<td>CL</td>
<td>BEGIN(H,R,question(b)) Can I ask you a question?</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,question(b)) Yes, sure.</td>
</tr>
<tr>
<td>d1:s1</td>
<td>question(H,R,b) Is it a red box?</td>
</tr>
<tr>
<td>CL</td>
<td>PROPOSE-RETURN-CONTROL(R,H)</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,RETURN_CONTROL)</td>
</tr>
<tr>
<td>CL</td>
<td>BEGIN(R,H,question(c)) Can I ask a related question?</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,question(c)) Absolutely.</td>
</tr>
<tr>
<td>d2:s1</td>
<td>question(R,H,c) Did you already find a red box?</td>
</tr>
<tr>
<td>d2:s2</td>
<td>assert(R,H,c) Yes, I did.</td>
</tr>
<tr>
<td>d2:s3</td>
<td>accept(R,H,c) Ok.</td>
</tr>
<tr>
<td>d2:f1</td>
<td>END(INFO-SEEK(c)) terminate dialogue d2</td>
</tr>
<tr>
<td>CL</td>
<td>PROPOSE-RETURN-CONTROL(R,H)</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,RETURN_CONTROL)</td>
</tr>
<tr>
<td>d1:s2</td>
<td>assert(R,H,¬b) No, it is not a red box.</td>
</tr>
<tr>
<td>d1:s3</td>
<td>challenge(H,R,¬b) Why is it not a red box?</td>
</tr>
<tr>
<td>d1:s4</td>
<td>assert(R,H,S(¬b)) Because there is only one red box in our world, and we already found it.</td>
</tr>
<tr>
<td>d1:s3</td>
<td>accept(H,R,¬b) Ok, this is not the red box.</td>
</tr>
<tr>
<td>d1:f1</td>
<td>END(INFO-SEEK(b)) terminate dialogue d2</td>
</tr>
<tr>
<td>CL</td>
<td>END(CONTROL) terminate all dialogues</td>
</tr>
</tbody>
</table>
Example 5: Parallel dialogues

<table>
<thead>
<tr>
<th>current state</th>
<th>dialogue move</th>
</tr>
</thead>
<tbody>
<tr>
<td>CL</td>
<td>BEGIN(H,R,question(b)) Can I ask you a question?</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,question(b)) Yes, sure.</td>
</tr>
<tr>
<td>d1:s1</td>
<td>question(H,R,b) Is it a red box?</td>
</tr>
<tr>
<td>CL</td>
<td>PROPOSE-RETURN-CONTROL(R,H)</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(H,R,RETURN_CONTROL)</td>
</tr>
<tr>
<td>CL</td>
<td>BEGIN(R,H,question(c)) Can I ask a completely separate question?</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(R,H,question(c)) Absolutely.</td>
</tr>
<tr>
<td>d2:s1</td>
<td>question(H,R,c) Is it a blue ball?</td>
</tr>
<tr>
<td>CL</td>
<td>PROPOSE-RETURN-CONTROL(R,H)</td>
</tr>
<tr>
<td>CL</td>
<td>AGREE(H,R,RETURN_CONTROL)</td>
</tr>
<tr>
<td>d1:s2</td>
<td>assert(R,H,¬b) It is not a red box.</td>
</tr>
<tr>
<td>d1:s3'</td>
<td>challenge(H,R,¬b) Why not?</td>
</tr>
<tr>
<td>d1:s4'</td>
<td>assert(R,H,S(¬b)) Because it is red, but not rectangular.</td>
</tr>
<tr>
<td>d1:s3'</td>
<td>accept(H,R,¬b) Ok, it is not a red box.</td>
</tr>
<tr>
<td>d1:f1'</td>
<td>END(INFO-SEEK(b)) terminate dialogue d1</td>
</tr>
<tr>
<td>d2:s2</td>
<td>assert(R,H,c) Yes, it is a blue ball.</td>
</tr>
<tr>
<td>d2:s3</td>
<td>accept(H,R,c) Ok, we found the blue ball.</td>
</tr>
<tr>
<td>d2:f1</td>
<td>END(INFO-SEEK(c)) terminate dialogue d2</td>
</tr>
<tr>
<td>CL</td>
<td>END(CONTROL) terminate all dialogues</td>
</tr>
</tbody>
</table>

4.3 Experimental Domain: The Treasure Hunt Game

This research adopts a modified Treasure Hunt Game (THG) as an experimental search domain. It has been used as a controlled urban search and rescue experimental environment for studying
human-robot interaction [Lewis et al., 2003; Marge et al., 2009]. A THG played in a treasure search domain encourages co-ordination and collaboration between team members [Jones et al., 2006]. The THG adopted in this thesis is a variation of the treasure hunt domain introduced in [Jones et al., 2006] where the objective is for each robot-robot team to maximize the amount of treasure collected within a fixed period of time.

Our version of the treasure hunt game [Sklar and Azhar, 2015] involves two types of players: a human player and a single robot player. It frames the search domain as a real-time strategy game. The goal is for the human and a robot to form a collaborative team and to locate objects, or “treasures,” in a physical environment, or “arena,” that is accessible to the robot but not to the human. This domain is defined in this research as a “game” because the robot has limited resources and because time is a factor. The robot cannot simply perform an exhaustive search of the arena to find all the treasures. Thus, the human and the robot have to decide collaboratively how best to make use of those resources and locate as many treasures as possible to maximize their scores. The robot does not return the treasures to the home location since the robot deployed for this research does not have manipulators. The robot operates inside the arena with the ability to move around the arena, use sensors (cameras or range sensors) to gather information about the arena, and remotely communicate that information to the human player. The human operates outside the arena and has the ability to remotely receive limited information from the robot about the arena and to communicate with the robot. The human remotely requests that the robot visit “interest points” (particular locations in the arena) and gather sensor data. Thus the human-robot interaction during our modified treasure hunt game is a remote interaction since the human and the robot are in different locations and not in each other’s line of sight [Goodrich and Schultz, 2007].

The robot has an energy level associated with it that decreases as the robot performs the following actions:

- When the robot moves, it expends energy and health points decrease.

- When the robot gathers sensor data, it expends energy, and health points decrease.
• When the robot transmits sensor data to the human, it expends energy, and health points decrease.

The shared mission of the game in our modified treasure search domain is for the human to find and correctly identify as many treasures in the arena as possible before the robot loses its health points. The human-robot team’s score in the game is the number of points earned by correctly identifying treasures.

The remainder of this section provides a formal description of our modified THG as we documented in [Sklar and Azhar, 2015].

Each game is defined by the following tuple:

\[
\langle \text{map, treasures, obstacles, tasks, dependencies, robots} \rangle
\]

In the case of the experiments described here, the following definitions are used.

### 4.3.1 Map

A map is a tuple \((\text{size, walls})\) as defined in [Sklar and Azhar, 2015].

### 4.3.2 Treasures

For each round of the THG, a different set of treasures is defined:

\[
\langle \text{type, roomID, } x_i, y_j \rangle
\]

where:

- \text{type} is the type of treasure item (e.g., “cube” or “bottle”);
- \text{roomID} is the room number in the map where the treasure is located; and
\( (x_i, y_i) \) is a point in the polygon that describes the treasure item’s footprint.

Here are two sample sets of treasures:

- **Treasure Set 1:**
  - orangeBottle 1 100 437
  - blueBottle 2 313.5 437
  - yellowCan 3 480 103
  - pinkCan 4 100 103

- **Treasure Set 2:**
  - pinkCan 3 480 437
  - yellowCan 1 100 437
  - orangeBottle 6 480 103

### 4.3.3 Tasks

The simple collaborative task is for the human-robot team to find the maximum number of treasures within the least amount of time. The robot is capable of performing the following tasks:

- **path-planning** = the robot determines an efficient path plan in which the robot visits all rooms that it needs to visit using the A* algorithm [Hart et al., 1968].

- **sensor-sweep** = the robot rotates in-place and uses its camera to capture a sequence of images in a 360° arc and sends them to the system from a location within the currently visited room; and

- **object-identification** = the human collaborator analyzes an image the robot has captured and attempts to identify a particular object in the image.
4.3.4 Dependencies

The following dependency exists between the types of tasks defined above:

- the path-planning task must be performed before a sensor-sweep task when the location in which the sensor-sweep task is assigned to take place is different from the robot’s current location.

- a sensor-sweep task must be performed before an object-identification task.

4.3.5 Robots

A robot is defined by the tuple:

\[
\text{robot} = < \text{id}, \text{type}, r, x_0, y_0, \theta_0 >
\]

where:

- \( \text{id} \) = unique identifier (i.e., name or number)
- \( \text{type} \) = “Blackfin”
- \( r \) = the radius of the robot’s footprint starting location \((x_0, y_0, \theta_0)\).

4.3.6 Score

The human-robot team receives a score for the mission based on the number of correctly identified treasures. Each treasure has a value associated with it. In the experiments described in chapters 6 and 7, we employed the following scoring mechanism. When the human correctly locates a treasure, 400 points are earned. 150 points are deducted for not finding a treasure or misidentifying a treasure. The score for each game played by human participants is recorded.
4.4 Experimental Methodology

This section details the experimental methodology employed in investigating the overall goal of this thesis: measuring the system performance and user experience of adding peer interaction through argumentation based-dialogue to an HRI system and comparing it to an HRI system capable of only supervisory interaction with minimal-dialogue.

In the remainder of this section, peer interaction enabled through argumentation-based dialogue is labeled as full-dialogue, and minimal-dialogue refers to dialogue that is conducted during supervisory interaction in which the robot follows human commands only.

Experimental Dialogue Mode:

Human participants are exposed to two experimental conditions:

A. full-dialogue mode with argumentation-based dialogue theorized and formalized in Section 4.1 and Section 4.2 for human-robot collaboration. In full-dialogue mode during peer interaction a robot or human can acquire new information from each other when one does not know something and inquire together to discover new information when neither has complete information about a subject matter. Both humans and robots can challenge or persuade each other, if there is a disagreement (i.e., conflicting beliefs) about preventing human or robot errors or reducing task competition time. In full-dialogue mode, humans and robots can converse as partners about what the robot should do and reach agreement before the robot takes any actions; and

B. a minimal-dialogue mode without argumentation-based dialogue. In minimal-dialogue mode a human provides supervisory commands to the robot and the robot obeys. Sharing or expanding knowledge is not supported in minimal-dialogue mode. There is no disagreement since a human, as supervisor, is the sole decision-maker. The minimal-dialogue mode is the baseline mode for a comparison with the full-dialogue mode.
**Human-Robot Collaboration Mode:**

This research recognizes the following two kinds of collaborations for each dialogue mode during a collaborative game in the treasure search domain.

- *Supervisory Collaboration* employing *minimal-dialogue mode*: In this mode, humans, acting as supervisors, work with robots and are solely responsible for all shared-decision making. The robot provides no feedback since it is required to obey the human during supervisory collaboration. Thus, the *minimal-dialogue* support is provided during supervisory collaboration where the robot can act only as a subordinate following the human’s command. It is incapable of providing feedback.

- *Peer Collaboration* employing *full-dialogue mode*: In this mode, the human collaborates with the robot as a peer, and the robot is capable of providing feedback to the human. Thus, full-dialogue support is provided during peer collaboration where the robot and the human may share or expand knowledge or challenge or persuade each other to resolve disagreement in a given context.

**Human-Robot Shared-Decision Making:**

The common goal of both human and robot in our modified treasure hunt game is to complete the shared task of finding the maximum number of treasures in the minimum amount of time following the game rules described in Section 4.3. This research identifies three types of shared-decisions the human and the robot may collaboratively make during a treasure hunt game play scenario: (1) deciding “where to search” for treasures; (2) deciding “how to get there” (i.e., which room-search order to use); and (3) deciding “what is found there” in each room once the robot arrives (i.e., identifying treasure by analyzing images collected by the robot).
4.4.1 Full-Discussion Mode

Full-dialogue mode employs argumentation-based dialogue based on our Argumentation-based Dialogue Framework and allows the robot to engage in information-seeking, inquiry, and persuasion dialogue as described in Section 4.2.1.

Identifying Opportunities for Full Dialogue:

We identify three different full-dialogue opportunities are identified in my research for each shared-decision making (i.e., where to search, how to get there, what is found there) in our treasure hunt game as in Figure 4.8. Each decision is preceded by a belief setup, which is required to trigger an argumentation-based dialogue as full dialogue.

![Figure 4.8: Opportunities for Full Dialogue in a Treasure Hunt Game](image)

1. Discuss “where to search?”: First, the robot and the human collaborator need to discuss “where to search in the THG map to find the treasure(s).”

A Game Master software application is introduced to set up the game and manage the treasure hunt game as defined in Chapter 5. The Game Master is a built-in feature that is
added to support experimentation for my thesis. It is to ensure that we can demonstrate and
test all three kinds of dialogues during “where to search?” discussion. As soon as the game
starts, the game master may randomly provide clue(s) to the robot during the first decision
round. The robot’s belief \( (b \in \Delta_R) \) is initially updated based on the information provided by
the game master. There are two scenarios:

1. If the game master provides a clue to the robot, the robot will update its beliefs as
   follow:
   - The robot knows “where to search” and sets the value for \( b \in \Delta_R \) since it has been
given a clue(s) by the game master.

2. If the game master does not provide a clue to the robot, the robot will then update its
   beliefs as follows:
   - The robot does not know “where to search” and sets the value for \(?b \in \Delta_R\) since
   it has not been given a clue(s) by the game master.

The information about the human’s belief is recorded from the human participant to update
the robot’s belief about the human’s belief \( (\Gamma_R(H)) \). The human collaborator may choose
one of the following:

(a) *I know where to send the robot to find treasures*: If the human collaborator chooses this
   option, there are two possibilities:
   - the robot and the human collaborator believe the same; therefore, they are in agree-
   - the robot believes \( b \) and human believes \( \neg b \), therefore, they are in disagreement
   and a persuasion dialogue will be triggered. This will set the belief value for
\( \neg b \in \Gamma_R(H) \).

(b) *I do not know where to send the robot to find treasures*: If the human collaborator
   chooses this option it will set the robot’s belief value of the human’s belief for \( ?b \in \)
\( \Gamma_R(H) \). This scenario provides opportunities for either information-seeking or inquiry dialogue as explained in the Table 4.11.

The Table 4.11 summarizes the possible types of argumentation-based dialogues to discuss “where to search,” based on the information from the game master and the belief inputs from the human participant.

<table>
<thead>
<tr>
<th>Case</th>
<th>b ∈ ( \Delta_R )</th>
<th>( \neg b \in \Delta_R )</th>
<th>?b ∈ ( \Delta_R )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>agreement</td>
<td>disagreement</td>
<td>lack of knowledge</td>
</tr>
<tr>
<td>2</td>
<td>(no dialogue)</td>
<td>persuasion</td>
<td>persuasion</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>information-seeking</td>
</tr>
<tr>
<td>4</td>
<td>disagreement</td>
<td>agreement</td>
<td>no dialogue</td>
</tr>
<tr>
<td>5</td>
<td>persuasion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td>information-seeking</td>
</tr>
<tr>
<td>7</td>
<td>lack of knowledge</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>information-seeking</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>information-seeking</td>
<td></td>
<td>inquiry</td>
</tr>
</tbody>
</table>

Table 4.11: Possible pre-conditions and corresponding Argumentation-based Dialogues for discussing where to search

The human collaborator and the robot discuss “how to get there” after finishing discussing and deciding on “where to search.”

2. Discuss “how to get there?” (Plan): The robot and the human collaborator discuss and decide on “how to travel the map to find the treasures” next.

The robot in our treasure hunt search domain is designed to know how to create a plan to visit the target locations selected. This provides opportunities for the human and the robot to engage in high-level decision making about “how to get there” employing full dialogue. Therefore, the robot’s belief is set as follows:

- The robot knows “how to travel around the map to find the treasures,” which will set the belief value for \( b \in \Delta_R \).
The information about the human’s beliefs is collected to update the robot’s beliefs about the human’s beliefs $\Gamma_R(H)$. The human collaborator may choose one of the following:

(a) *I know how the robot should navigate the THG map to find treasures*: If the user chooses this option, it will set the robot’s belief about the human’s belief value for $b \in \Gamma_R(H)$. According to the preconditions in Table 4.12, a *persuasion dialogue* will be triggered where the user chooses the order in which the robot should travel to selected locations based on the decision during “where to search.” We describe an “agenda” as an ordered list of “tasks” that the robot will attempt to achieve. Like the human participant, the robot interacting with the human participant as a peer in full-dialogue mode is required to be able to formulate its own agenda to engage in shared decision-making. The robot’s agenda is based on its current location and amount of battery power. The battery power influences the number of rooms the robot can visit at the beginning of the game.

(b) *I don’t know how the robot should navigate the THG map to find treasures*: If the user chooses this option, it will set the robot’s belief about human’s belief value for $b \in \Gamma_R(H)$. This scenario provides opportunities for an information-seeking dialogue for the human participant, as explained in Table 4.12.

The Table 4.12 summarizes the possible types of argumentation-based dialogue to discuss “how to get the there” based on the updated robot’s beliefs and robot’s beliefs about the human collaborator’s beliefs.

If the robot’s agenda is different from the human’s agenda, an explanation is given in the form of text-based dialogue. Please note that the robot’s agenda is based on its current location and amount of battery power. The human then has the option of agreeing or disagreeing with the robot’s agenda. If the human agrees, the robot executes its own agenda; otherwise, the

---

2 The battery power is simulated in the software because the current physical robot used in this experiment does not provide reliable information about its battery power.
Table 4.12: Possible pre-conditions and corresponding Argumentation-based Dialogues for discussing how to get there

<table>
<thead>
<tr>
<th>Case</th>
<th>b ∈ Γₚ(H)</th>
<th>¬b ∈ Γₚ(H)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>agreement</td>
<td>disagreement</td>
</tr>
<tr>
<td>2</td>
<td>persuasion</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>lack of knowledge</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>persuasion</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>agreement</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>lack of knowledge</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>information-seeking</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>information-seeking</td>
<td></td>
</tr>
</tbody>
</table>

robot accepts the human’s agenda, obeying the three laws of robotics [Asimov, 1950].

3. The robot will visit those locations from the map that the human player and the robot agree on.

4. The robot visits the interest points and takes pictures (performs a sensor sweep).

5. Each sensor sweep produces a fixed set of pictures of the arena, for each set of treasures, and these pictures are sent to the human to discuss the “identity of the treasures.” Not all pictures have treasures in them. The pictures of the assigned treasure set taken and saved prior to the experiment are used to prevent experimental failure due to robot camera failure.

6. Discuss the “identity of the treasure” (Identification): The robot does not know how to identify the treasure and relies on the human collaborator’s image analysis capabilities to discuss the “identity of the treasure.” The robot, however, will have the following partial set of beliefs that may be used during dialogue:

   - The robot will know colors present in each image. This information can be utilized during inquiry dialogue if the human collaborator cannot detect the color.
   - The robot will know which treasures have already been identified in which location of the arena. The robot will also know that each type of treasure only appears once
according to the rules of the THG. The robot may challenge the human collaborator in case the human mistakenly identifies an already found treasure.

Therefore, the robot’s belief will be set as follows:

- As the robot does not know “how to identify the treasure” it’s belief value will be set to \(?b \in \Delta_R\). According to our ArgHRI framework, the robot’s knowledge about colors in the images or the identity and the location of already found treasures are partial beliefs about the identity of a treasure. Therefore, the belief will be labeled as \(?b \in \Delta_R\).

- The human collaborator knows “how to identify the treasure” which will set the robot’s belief value of the human’s belief for \(b \in \Gamma_R(H)\).

- The human collaborator does not know “how to identify the treasure,” which will set the robot’s belief value of the human’s belief for \(?b \in \Gamma_R(H)\). This scenario provides opportunities for inquiry dialogue given that the robot also does not know “how to identify the treasure” but may have partial information about the treasures, as explained in the Table 4.13.

Table 4.13 describes the possible types of argumentation-based dialogue available to discuss “the identity of the treasure” based on the updated robot’s beliefs and robot’s beliefs about the human collaborator’s beliefs.

During the information-seeking dialogue, the human collaborator can decide whether an image contains a treasure and if so, the human should label that image and submit it to the game master for the assessment.

7. If the human-robot team has correctly identified a treasure (and its location), then the human-robot team receives points for finding that treasure.

8. If the human-robot team incorrectly identifies a treasure, then the human-robot team loses points.
Table 4.13: Possible pre-conditions and corresponding Argumentation-based Dialogues for discussing the identity of the treasure

<table>
<thead>
<tr>
<th>Case</th>
<th>Pre-condition</th>
<th>Dialogue Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>( b \in \Gamma_R(H) )</td>
<td>lack of knowledge information-seeking</td>
</tr>
<tr>
<td>6</td>
<td>( \neg b \in \Gamma_R(H) )</td>
<td>lack of knowledge information-seeking</td>
</tr>
<tr>
<td>9</td>
<td>( ?b \in \Gamma_R(H) )</td>
<td>shared lack of knowledge inquiry</td>
</tr>
</tbody>
</table>

9. If the human collaborator cannot decide whether an image contains a treasure during the information-seeking dialogue, then the information-seeking dialogue will be terminated and an inquiry dialogue will be triggered. During the inquiry dialogue, the human collaborator can attempt to decide again whether an image contains a treasure given color information provided by the robot, and if so, the human should label that image and submit it to the game master for assessment.

10. If the human-robot team has correctly identified a treasure (and its location), then the human-robot team receives points for finding that treasure.

11. If the human-robot team incorrectly identifies a treasure, then the human-robot team loses points.

### 4.4.2 Minimal-Dialogue Mode

The minimal-dialogue mode is the baseline mode to which the full-dialogue mode is compared. This mode does not employ argumentation-based dialogue or other dialogue managers and is identical to traditional command-mode. Here, the human player exclusively decides what the robot should do during “where to search,” “how to get there” and “what is found there,” and the robot obeys these commands. Therefore, unlike full-dialogue mode, minimal-dialogue mode does not
allow the robot or the human participants to seek new information from each other when one
does not know something (i.e., lack of knowledge) or inquire together to acquire new information
when both have incomplete information about a subject matter (i.e., shared lack of knowledge).
In this mode, the robot cannot take the initiative and does not have the capability of challenging
or persuading the human player, if there is disagreement about preventing errors or reducing task
completion time.

The next Chapter 5 details the design and the implementation of our human-robot system called
ArgHRI, which is capable of argumentation-based dialogue support between a human and robot for
shared decision-making about their joint actions by applying the logic-based theoretical dialogue
framework described in this chapter.
Chapter 5

ArgHRI System: A Live HRI System

In this chapter, I present the design and the implementation of a human-robot system called ArgHRI where a human and robot can make decisions together by engaging in an argumentation-based dialogue about their joint actions. The ArgHRI system also provides experimental support for investigating the overall goal of this thesis.

The remainder of this chapter is structured as follows: Section 5.1 details the ArgHRI system design; Section 5.2 provides the ArgHRI system architecture; Section 5.3 describes the design and development of the ArgHRI human-robot user interface; and Section 5.4 details the phases of the ArgHRI software development.

5.1 System Design

The ArgHRI system is designed to support argumentation-based dialogue and human-robot collaboration experimentation as follows:

- **Argumentation-based Dialogue Support for Human-Robot Collaboration:** The ArgHRI system applies the theoretical ArgHRI framework and argumentation-based dialogue games detailed in Chapter 4 to provide argumentation-based dialogue support for open communications between a human and a robot. Argumentation-based dialogue support between a
human and robot is provided during a collaborative task by implementing the following in the ArgHRI system:

– *information-seeking dialogue* to support sharing knowledge,
– *inquiry dialogue* to support knowledge expansion, and
– *persuasion dialogue* to support conflict resolution.

**Experimental Support:** The ArgHRI system provides experimental support in the Treasure Hunt Game domain to investigate the following:

– **Experimental Dialogue Mode Support:** Two different dialogue modes are implemented to investigate the impact of adding peer interaction through argumentation-based dialogue to an HRI system. The ArgHRI system provides support for two experimental modes:
  * a *full-dialogue mode* in which the human collaborator communicates with the robot as a peer [Scholtz, 2003] through *argumentation-based dialogues*, and
  * a *minimal-dialogue mode* in which the human collaborator, acting in a *supervisory* role, commands the robot [Scholtz, 2003] without discussion.

– **Treasure Hunt Game Domain Support:** The ArgHRI system allows a human and a robot to play our modified Treasure Hunt Game (THG) [Azhar et al., 2013b] in the Treasure Hunt Game domain where players can make decisions about their joint actions with or without using argumentation-based dialogue. The common goal of the human and robot in our modified THG is to complete the shared task of finding the maximum number of treasures in the minimum amount of time expending least energy, following the game rules described in Section 4.3.

– **Data Collection Support:** The ArgHRI System supports the collection of data for experimentation while a human and robot play our modified THG.
5.2 System Architecture

The ArgHRI System consists of an internal core system and two external systems that support argumentation-based dialogues between a human and robot. The ArgHRI internal core system has three major internal modules:

- The User Interface Manager module manages displaying all relevant information in the ArgHRI User Interface, which is required for a human collaborator to interact with a robot for a given shared task.

- The Dialogue Manager module manages all dialogue-related events that occur between a human and robot.

- The Robot Manager module manages robot-related events, including simulating the robot in the ArgHRI Graphical User Interface, which communicates between the HRTeam system and the User Interface Manager module.

The ArgHRI system employs two existing external systems to support the ArgHRI core system, as shown in Figure 5.1:

- The ArgTrust [Tang et al., 2012a] argumentation engine provides support for argumentation-based dialogues.


The ArgHRI system integrates an experimental module to support experiments required for the research presented in this thesis. The experimental module include two additional modules that work with the ArgHRI internal core system:

- The Game Manager module manages game-related events during an individual THG.
The Log Manager module logs events from the User Interface Manager, Dialogue Manager, and Game Manager modules.

Figure 5.1: ArgHRI System Architecture

The remainder of this chapter is structured as follows: Section 5.2.1 discusses the ArgHRI core system. The integration of ArgHRI and ArgTrust is discussed in Section 5.2.2; followed by a discussion about the integration of the ArgHRI and HRTeam in Section 5.2.3. Section 5.2.4 details the experimental modules.

5.2.1 ArgHRI Core System

- **User Interface Manager**: The ArgHRI User Interface Manager primarily manages the five different interface panels, as shown in Figure 5.2 and communicates with the other ArgHRI modules.

  A. **Map Panel**: The User Interface Manager module ensures that the correct map is drawn in the map panel using a configuration file that is designed to simulate a proportionally physical arena inside the ArgHRI interface. The interface module draws the robot’s up-
to-date location on the map panel by communicating with the Robot Manager module and the HRTeam server during a THG.

B. Image Panel: The User Interface Manager module displays the five most recent images from the rooms last visited by the robot communicating with the Robot Manager Module.

C. Dialogue History Panel: The User Interface Manager module manages the history of current and past dialogues between the robot and the human collaborator and displays them in the dialogue history panel by communicating with the Dialogue Manager module.

D. Dialogue Panel: The User Interface Manager module provides the required dialogue contents in the ArgHRI interface for the human collaborator to engage in a dialogue with a robot by communicating with the Dialogue Manager module.

E. Game Status Panel: The User Interface Manager module displays up-to-date game scores, the robot’s simulated health, and treasure data found during each THG game by communicating with the Game Manager module.

The design and development of the ArgHRI User Interface is discussed in Section 5.3.

- **Dialogue Manager Module**: The ArgHRI Dialogue controls all human-robot dialogues and dialogue-related events during a Treasure Hunt Game in both *peer* and *supervisory* interaction. The primary dialogue-related events during *minimal-dialogue* include scripted dialogue content and dialogue history. The major dialogue-related events during *full dialogue* include types of argumentation-based dialogues, dialogue moves, scripted chat-style dialogue content for each dialogue move, and dialogue history from the commitment store (*CS*). All full-dialogue events apply the dialogue protocols and theoretical framework described in Chapter 4.

The Dialogue Manager Module generates appropriate argumentation-based dialogues during
different dialogue opportunities (i.e., “where to search,” “how to get there,” and “what is found”) identified in the THG experimental domain detailed in Chapter 4. As shown in Figure 4.8, each decision is preceded by the belief setup in the ArgHRI interface, which is required to trigger an argumentation-based dialogue that is also managed by the ArgHRI dialogue manager.

The Dialogue Manager module supports three types of argumentation-based dialogues: persuasion dialogues, inquiry dialogues, and information-seeking dialogues that are implemented by applying the theoretical framework [Azhar, 2012; Sklar et al., 2013b; Sklar and Azhar, 2015] detailed in the Chapter 4. The protocol for each type of dialogue determines the allowable set of responses for each opening and subsequent move. The Dialogue Manager also maps each argumentation-based dialogue move (e.g., question(b), challenge(b)) to the corresponding scripted text, as shown in Figure 5.3. The Dialogue Manager ensures that the robot’s beliefs and its beliefs about the human’s beliefs are updated after the termination of each argumentation-based dialogue.

The Dialogue Manager maintains a knowledge base of rules and facts as well as maintaining
beliefs (e.g., the robot’s beliefs and the robot’s beliefs about the human collaborator’s beliefs) for the argumentation-based dialogues. The Dialogue Manager communicates with ArgTrust using XML files, with the help of a parser module to support argumentation-based dialogue processing as described in Section 5.2.2.

- **Robot Manager Module**: This module supports the domain dependent ontology that describes the robot’s actions and capabilities employed in our ArgHRI framework. In a traditional multi-agent dialogue environment, virtual agents are instantiated in software, and their actions can be deterministic because of less noisy virtually noiseless software environments. The action of robots and physical agents, however, are non-deterministic because they are embodied in the noisy and dynamic physical world. We extend Nilsson [1984]’s classic robot control structure by adding dialogue steps to the original steps: sense, plan, and act, as shown in Figure 5.4 step 2* to enable discussion between a robot and a human before planning about action. Sensing refers to extracting information from the robot’s environment; planning requires the robot to decide what to do next based on sensory inputs; and acting
Figure 5.4: Robot control architecture, with dialogue step added. [Sklar and Azhar, 2015]

requires the robot to execute its plan.

The ArgHRI implements the processing steps shown in Table 5.1 [Sklar and Azhar, 2015]. The Robot Manager module also communicates with the HRTeam software to allow the human and the robot to play a game in the Treasure Hunt Game domain.

---

### Table 5.1: The Processing steps of our modified robot control structure [Sklar and Azhar, 2015].

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S.</td>
<td>The robot $R$ starts with an initial belief state: $R.\Sigma_0$ (at time $t = 0$)</td>
</tr>
<tr>
<td>1.</td>
<td>The robot $R$ senses its environment, at time $t$: $R.\text{obs}<em>t \leftarrow R.\text{sense}(Env_t)$ and then updates its prior beliefs, based on its observations: $R.\Sigma_t \leftarrow \text{update}(R.\Sigma</em>{t-1}, \text{obs}_t)$</td>
</tr>
<tr>
<td>2.</td>
<td>The robot $R$ plans which action to perform: $R.\text{Act}_t \leftarrow \text{action}()$</td>
</tr>
<tr>
<td>2*.</td>
<td>The robot $R$ discusses its plan with human $H$ to reach agreement: $R.\text{Act}_t \leftarrow R.\text{dialogue}(H)$ The plan may change or stay the same. Re-sense (step 1) and re-plan (steps 2 and 2*), if necessary (i.e., if the environment has changed).</td>
</tr>
<tr>
<td>3.</td>
<td>The robot $R$ performs the selected action, $R.\text{Act}_t$.</td>
</tr>
<tr>
<td>4.</td>
<td>The process iterates back to step 1.</td>
</tr>
</tbody>
</table>

---

### 5.2.2 Integration of ArgHRI and ArgTrust

The ArgHRI system integrates ArgTrust [Tang et al., 2011a] as its back-end argumentation engine to support argumentation-based dialogues. The parser module of the ArgHRI system works with the Dialogue Manager module and is responsible for processing input sent from the ArgHRI system to the ArgTrust and output generated from ArgTrust to the ArgHRI system. The parser is also
capable of maintaining (e.g., adding, deleting) the robot’s beliefs when needed. It is described by the memory system of our framework.

The ArgTrust engine takes as input an XML file that describes an agent’s set of beliefs about the world, about its environment, and about other agent(s) with which it is interacting and represents them as facts, predicates, and rules. The XML file includes the desired query about the agent's belief that will be evaluated by the ArgTrust engine [Parsons et al., 2011]. In our Treasure Hunt Game domain, the agents are the robots in the experimental environment as well as the human collaborators interacting with the system. The input XML file contains all the robot’s beliefs and its beliefs about the human collaborator’s beliefs, as outlined in our theoretical model (described in Chapter 4). The ArgTrust engine has been modified to output an XML file to the ArgHRI system with a response to the input query. The ArgTrust engine highlights any conflicts that may exist in the set of beliefs relevant to the query for the ArgHRI system.

The ArgTrust engine applies a “labeling technique” [Baroni et al., 2011; Caminada and Gab-bay, 2009] to indicate the status of an argument: IN to indicate the acceptance of an argument, OUT to indicate the rejection of an argument, UNDEC to undecide an argument due to conflict of beliefs (i.e., neither accepted nor rejected) [Tang et al., 2012b]. This follows a traditional logic semantic model. To properly inform the user about why there is a conflict, it is typically useful to know why an argument should be rebutted. Thus the ArgTrust output file includes which rules or beliefs caused conflicts.

Appendix A contains a sample XML input file from the ArgHRI system that queries the ArgTrust argumentation engine about whether the robot should go to room 2 (e.g., GoTo (Room2)). ArgTrust outputs another XML file with an answer to the input query, highlighting any conflicts that might exist in the set of beliefs relevant to the query. Appendix A also contains an example in which the status of the query argument “GoTo(Room2)” is UNDEC, which indicates a conflict of beliefs between the robot and the human collaborator. The ArgHRI Dialogue Manager will trigger a persuasion dialogue in this scenario.
5.2.3 Integration of ArgHRI and HRTeam

This section describes the integration of the ArgHRI core system and the HRTeam human/multi-robot team framework [Sklar et al., 2013d].

HRTeam is a framework that supports experimentation with mixed-initiative human/multi-robot teams [Sklar et al., 2011]. It can support human/multi-robot interaction. The robots can operate in the physical world or in a simulated, virtual environment. HRTeam has a central server that coordinates communication among HRTeam software modules and information databases and supports communication with the ArgHRI system. The HRTeam software modules include robot controllers, as well as camera agents that provide localized position information for robots in the physical HRTeam environment. As discussed earlier, in the ArgHRI Robot Manager module, the dialogue step is added in the robot controller loop (see Figure 5.4) to enable the robot to engage in dialogue with the human collaborator, before making shared decisions (i.e., “where to search,” “how to get there,” and “what is found there”) in the THG.

The HRTeam already has a representation of the robot’s world (a “map”), the notion of “interest points” within that world, and an achievement task that involves visiting an interest point. In the current HRTeam setup, both minimal-dialogue robot and full-dialogue robot use the A* [Hart et al., 1968] path planning algorithm to find the shortest path between two points during physical and simulation experiments. The robot then uses greedy shortest-path reasoning to determine the order in which it will visit multiple points to determine the preferred task order. The HRTeam system has been modified to allow an ArgHRI system operator to override a robot’s preferred task order with a manually chosen one proposed by the human collaborator during the following human-robot collaborative scenarios:

- The robot’s preferred task order is overridden by the human’s preferred task if the human collaborator takes a supervisory role [Scholtz, 2003] and engages in a dialogue in minimal-dialogue mode with the robot. In the minimal-dialogue mode, the robot obeys the human collaborator’s commands and does not challenge or persuade.
• The robot takes the peer role [Scholtz, 2003] and engages in a persuasion dialogue in full-dialogue mode with the human collaborator to persuade the human about its preferred task order. If the human disagrees with the robot and is not persuaded, the robot’s preferred task order is overridden by the human’s initial proposed preferred task.

To support experimentation related to this thesis, the following data from the central server of HRTeam are collected (See Appendix A):

• *Deliberation Time*: Deliberation time is calculated by measuring the decision-making time for the collaborating robot and human for a task.

• *Task Completion Time*: Task completion time refers to the amount of time that the robot takes to complete a task.

### 5.2.4 Experimental Modules

The experimental modules include the following two modules, which are embedded within the ArgHRI Core System to support experimentation:

• **Game Manager Module:**

  The Game Manager module manages the virtual Game Master, which is responsible for setting up the game and managing each Treasure Hunt Game played between a human and a robot. The Game Master also randomly provides clue(s) for the robot’s choices about the “number of rooms to visit” at the start of a game during the full-dialogue mode “where to search” discussion. The ArgHRI Dialogue Manager then updates the robot’s beliefs \( b \in \Delta_R \) based on information provided by the Game Master. Any clues, provided by the Game Master provide opportunities for persuasion, information-seeking or inquiry dialogue during the “where to search” discussion as described below:

  – If the Game Master provides a clue to the robot, the robot will update its beliefs about “where to search” (i.e., \( b \in \Delta_R \)).
If the human also knows “where to search” and the robot and human disagree, then a persuasion dialogue is initiated where the robot, having received a clue from the Game Master, attempts to persuade the human collaborator.

If the human does not know “where to search”, then an information-seeking dialogue is initiated where the human can query the robot.

– If the Game Master does not provide a clue to the robot, the robot does not know “where to search” (i.e., $\exists b \in \Delta_R$).

Initially, an information-seeking dialogue is initiated at the point when the robot queries the human.

* If the human also does not know, then an inquiry dialogue is initiated where the robot and the human collaborator decide together.

The “I don’t know” selection option in the “where to search” dialogue panel enables the human collaborator to communicate lack of knowledge to the robot. The “I don’t know” selection option is provided to the human collaborator in the ArgHRI User Interface dialogue panels for the “where to search,” “how to get there,” and “what is found there” discussions. The Game Manager module updates game score data, robot’s simulated health data, and treasure-found data following the rules of our modified Treasure Hunt Game (detailed in Chapter 4).

**Log Manager Module:** This module is responsible, during each Treasure Hunt Game, for continuously logging the time, source, and description of various system events from the internal ArgHRI system modules. Log files are created at the beginning of each game. The core ArgHRI system events are recorded in three separate logs: the *game events log*, the *graphical user interface (GUI) events log*, and the *dialogue events log*.

The *game events log* includes dialogue mode, treasure set, game score, simulated robot’s health, and treasure-found data from the game master module. The log of the number of
treasures found and robot’s health is analyzed post game to compute the task success rate. The GUI events log data include user clickstream data signaled by the Interface Manager and Dialogue Manager modules. All dialogues are supported in the ArgHRI system through GUI labels, texts, and buttons in the interface. The clickstream game data from the human collaborator records which types of dialogues are used. The dialogue events log includes all human-robot dialogue-related data for each treasure hunt game. The data come from the Dialogue Manager and Interface Manager modules. Dialogue log data include the dialogue history. They also include the dialogue history mode, the number of information-seeking dialogues, the number of inquiry dialogues, the number of persuasion dialogues, the number of no-dialogues, the number of times that the argumentation-based dialogues are challenged by either a robot or a human, the number of times the full-dialogue terminated in agreement, and the number of times the full-dialogue terminated in disagreement. All the log data of the dialogue events collected and recorded by the Log Manager module during final user study are analyzed and reported in Chapter 7.4.

5.3 Human-Robot Interface

To design the Human-Robot Interface for the ArgHRI system, a User Centered Design [Adams, 2002] is adopted in my research, incorporating interface design principles from research in human-computer interaction (HCI) [Norman, 1990; Schneiderman, 2010] and interaction design guidelines from human-robot interaction [Adams, 2002; Scholtz, 2003]. A user-centered design approach requires understanding the target audience, user needs and requirements, as well as system tasks and goals [Adams, 2002]. The target audience for the ArgHRI human-robot interface is human participants primarily from academia who are assumed to be familiar with operating computing devices. The goal of the ArgHRI system is to provide a user-friendly environment where a human and robot can collaborate and engage in argumentation-based dialogue to make shared decisions. The characteristics of the Treasure Hunt Game domain are adopted from urban search and
rescue (USAR) application environment to design controlled experimental environment to study human-robot interaction [Baker et al., 2004]. Our modified Treasure Hunt Game experimental domain employs remote interaction like USAR application environments. Thus, the design of the ArgHRI User Interface incorporates the guidelines from [Adams, 2002; Baker et al., 2004; Keyes et al., 2010; Yanco et al., 2004] for designing effective interfaces for human-robot interaction in a USAR application.

The remainder of this section discusses the design principles [Adams, 2002] incorporated into the ArgHRI User Interface to enhance the human collaborator’s situational awareness (Section 5.3.1), lower cognitive load (Section 5.3.2), reduce human errors (Section 5.3.3), and aid human decision making (Section 5.3.4) during human-robot interaction.

### 5.3.1 Enhancing Situational Awareness

![Figure 5.5: The map panel of the ArgHRI Interface](image)

Designing Human-Robot Interfaces for remote robot operation demands carefully considering the interface so that it will enhance the human collaborator’s *situational awareness*. In the domain of human-robot interaction, the human collaborator’s ability to understand the robot’s abilities is characterized as *situational awareness* [Scholtz, 2003]. The graphical user interface for the system is the primary source of the human’s knowledge of the robot’s information during remote interac-
tion in a search domain [Keyes et al., 2010]. To facilitate situational awareness, the ArgHRI User Interface provides vital robot information to the human collaborator from our THG domain. Robot information includes game status, current robot location, robot movement, and images captured by the robot after it visits a room. As shown in Figure 5.5, a two-dimensional map panel is shown in the ArgHRI User Interface to illustrate the robot’s movement and determine its location during a game. A map-centric two-dimensional interface [Nielsen and Goodrich, 2006] is chosen since it can provide sufficient location awareness for remote robot interaction. To discuss the identity of the treasures effectively, the robot provides five images to the human collaborator after performing a sensor-sweep in a room. An image panel in the ArgHRI User Interface displays the most current images from the last room visited so that the human can review the five images and select the radio button for a particular image (e.g., image1, image2), as shown in Figure 5.6.

![Figure 5.6: The Image panel of the ArgHRI Interface](image)

The game status panel displays a continuously updated report of the robots simulated health status. According to the experimental protocol, as the game proceed the robots battery life diminishes and the robots health correspondingly declines. It also adds the game score and the number of treasures found, in the bottom panel of ArgHRI interface, as shown in Figure 5.7. All game-related
information is updated during the game based on the rules detailed in Chapter 4.

Figure 5.7: The Game Status panel of the ArgHRI Interface

5.3.2 Lowering Cognitive Load

The ArgHRI User Interface was designed to human collaborator’s cognitive load by reducing the workload to only those decisions that require high-level collaboration. The method of lowering cognitive load was introduced to aid the human collaborator’s concentration during the THG. The human collaborator interacts with the robot via the Human-Robot Interface to make high-level decisions about the THG. Three different types of high-level decisions are identified in our THG experimental domain: deciding “where to search,” deciding “how to get there,” and deciding “what is found there.” Deciding “where to search” involves discussing how many and which rooms the robot needs to visit from the rooms available to search. Deciding “how to get there” requires discussion about the order in which the robot needs to visit (or search) those rooms to find treasure. Deciding “what is found there” requires discussing the identity of a treasure (if any) by reviewing the images collected from rooms the robot has visited. The full-dialogue mode was designed to reduce the human collaborators memory load and increase exchange of information employing argumentation-based dialogue for “where to search,” “how to get there,” and “what is found there” decisions. A robot in the ArgHRI system autonomously visiting each selected room during the THG was designed to relieve the human collaborators level of involvement and reduce the human collaborator’s cognitive load.

5.3.3 Reducing Human Errors

Human errors are primary concerns when robots are collaborating with a human collaborator. Too many windows with too many options along with overwhelming information can overload the hu-
man collaborator, which can lead to human errors [Yanco et al., 2004]. The ArgHRI User Interface has two primary windows: a welcome window and the main game window where all human-robot interaction occurs. Thus with a small number of windows, the ArgHRI User Interface-related errors are likely reduced. In addition, the AgrHRI User Interface allows the robot to persuade or challenge the human collaborator’s error(s) (in full-dialogue mode. In the THG, human errors can be any of the following, for example:

- a human can propose a plan where a robot needs to visit all six rooms, which leads to a failed game because the robot does not have enough battery power to explore all requested rooms. In this case, if in minimal-dialogue mode, the game will end in failure. In full-dialogue mode, however, the robot is capable of preventing such human error by engaging in a persuasion dialogue to convince the human participant to change beliefs and provide a revised plan.

- In minimal-dialogue mode, a human can erroneously identify a treasure after reviewing an image shared by the robot during the THG. Although the robot does not know how to identify the treasure, the robot knows the color in each image. This information is utilized by the robot during inquiry or information-seeking dialogue in full-dialogue mode to challenge the human. For example, if there is no “red color” in any of the images shared by the robot and the human collaborator identifies a “red treasure,” then the robot will challenge the human collaborator to diagnose human errors.

5.3.4 Human Decision Making

High-level shared decision making support is provided in the ArgHRI system. It allows a human collaborator and a robot to engage in either minimal-dialogue or full-dialogue employing argumentation-based dialogue during “where to search,” “how to get there,” and “what is found there” discussions. As mentioned earlier, the ArgHRI system does not interpret or process natural
Figure 5.8: Anatomy of the ArgHRI Graphical User Interface

language to discuss those THG decisions because the research presented in this thesis is not focused on full natural language research, but rather on the types of argumentation-based dialogues that are required to convey task-specific information for effective human-robot communication. All dialogues between the human and the robot in both minimal-dialogue or full-dialogue mode are achieved by providing the human collaborator with multiple-choice style questions through labels and buttons in the ArgHRI User Interface. This interaction mode specifically enforces rule compliance by the human in the argumentation-based dialogue game, thus avoiding natural language issues. Exploration of natural language implementations of argumentation-based dialogue are left for future work. The different ArgHRI graphical user interface components designed to support human decision making during human-robot collaboration are described below:

- **Welcome Panel:** This is the first window the human collaborator encounters when the ArgHRI system starts (Figure 5.9), even before transitioning to the main window. This interface panel provides the Treasure Hunt Game rules, and selections for dialogue-mode, experimental environment, and treasure set. Selecting “Robot Mary” as a collaborator, enables the robot in minimal-dialogue mode, and it obeys commands given only by the human subject acting in a supervisory role [Scholtz, 2003]. Selecting “Robot Fiona” enables the robot in full-dialogue mode. Communication proceeds with the human using structured argumentation-
based dialogues in which the human and robot interact with each other as peers and reach agreement about the robot’s actions in the THG arena before actions are taken. In this panel, the experimental setup options also include selection for the “Simulation” or “Live Robot”. For example, selecting “Live Robot” connects the ArgHRI system to HRTeam operating in the physical robot environment. Finally, “Challenge 1” and “Challenge 2” selection allows switching between “Treasure Set 1” and “Treasure Set 2”. All these experimental dialogue modes and treasure set selections strictly follow the experimental protocol detailed in Section 4.3.

![Figure 5.9: ArgHRI System Welcome Window](image)

- **Dialogue History Panel:** A dialogue history is provided using a “chat” style interface to enhance human-robot dialogue in the upper right panel of the ArgHRI User Interface, as shown in Figure 5.10. This chat history panel aids human decision making by ensuring that the human collaborator can access past dialogues from the Treasure Hunt Game. The dialogue history is cleared when a new game starts.

- **Lack of Knowledge:** Expressing lack of knowledge about a topic to the collaborating partner is vital during shared-decision making. In the ArgHRI dialogue panels, the “I don’t know”
option is provided to the human collaborator to express a lack of knowledge for deciding “where to search,” “how to get there,” and “what is found there” in full-dialogue mode. When a human collaborator selects “I don’t know,” the pre-conditions are updated about the robot’s beliefs about the human’s beliefs to \( b \in R.\Gamma(H) \). This allows the human collaborator to seek information from the robot by either engaging in an information-seeking dialogue when the robot knows or inquiry dialogue when the robot does not know, all according to the dialogue protocols discussed in Chapter 4. As shown in Figure 5.12 (B), because the robot solely depends on the human collaborator during all decision making, the “I don’t know” option is not available when the human is acting in a supervisory role in minimal-dialogue mode during the “where to search” and “how to get there” discussions.

- *Deciding in the “where to search” dialogue panel:* The “where to search” dialogue panel is designed specifically for robot and human-collaborator decisions about how many rooms to visit and which rooms the robot needs to search for treasure in full-dialogue mode. The user is asked to enter beliefs about the number of rooms to search and which rooms to search for treasures. After the human collaborator and the robot decide on “where to search,” the system transitions to the “how to get there” panel in full-dialogue mode. The ArgHRI Dialogue Manager supports all three argumentation-based dialogues: persuasion, inquiry, and information-seeking.
The human’s inputs are stored in the ArgHRI system using the ontology described in the ArgHRI framework (Chapter 4).

- *Deciding in the “how to get there” dialogue panel:* In this full-dialogue panel, the user chooses the order in which the robot should travel to selected locations from the “where to search” discussion panel. We describe an “agenda” as an ordered list of “tasks” that the robot will attempt. The user can select an “I don’t know” option from the “how to get there” dialogue panel during full-dialogue mode only. The “I don’t know” option may trigger inquiry or information-seeking dialogue. While the user is interacting with the agenda planning dialogue panel, however, the robot is also formulating its own agenda during full-dialogue mode. In our ArgHRI System, the robot always knows how to make a plan in full-dialogue mode. Therefore, if the human participant chooses “I don’t know” during the “where to search” dialogue, an information-seeking dialogue will be triggered from the human collaborator to the robot.

The robot’s agenda is based on its current location and remaining battery power. The battery power influences the number of rooms the robot can visit. The battery power is sim-
ulated in the software because the current physical robot used in this experiment does not provide reliable information about its battery power.

During *minimal-dialogue* mode, the interface module presents a combination panel of “where to search” and “how to get there” discussion panels to the human collaborator as soon as the game starts (see Figure 5.12 (B)). In this minimal-dialogue mode planning dialogue panel, as shown in Figure 5.12 (B), the user is given a choice to select a plan choosing the rooms to visit and the order in which he or she wants the robot to travel to selected locations before asking the robot to execute the plan. There is no “I don’t know” option during planning in minimal-dialogue mode. The robot follows only the human collaborator’s agenda during minimal-dialogue mode. The human collaborator is required to plan the entire sequence of travel using the map and robot’s current location in the panel. It is based on the assumption that human participants are capable of spatial reasoning and utilizing common sense to decide feasible robot paths. Each human collaborator plays one game in minimal-dialogue and one game in full-dialogue mode as per our experimental design.

*Conflict Dialogue Panel*: The Conflict Dialogue Panel is designed to resolve conflicts be-
tween a human collaborator and a robot during persuasion dialogue. The interface module displays the Conflict Dialogue panel in full-dialogue mode during the “where to search” and “how to get there” discussions only when the ArgHRI system finds a conflict between the robot’s own beliefs and the robot’s beliefs about the human’s beliefs, which satisfies the pre-conditions to trigger a persuasion dialogue as described in the dialogue protocols detailed in Chapter 4. The ArgHRI system invokes the ArgTrust engine to assess the human’s beliefs and agenda in relation to the robot’s beliefs and agenda and to determine if any conflicts exist.

![ArgHRI Conflict Dialogue Panel](Figure 5.13: ArgHRI Conflict Dialogue Panel)

For example, if the robot’s agenda is different from the human’s agenda during the “how to get there” discussions, the robot proposes its alternate agenda to the human in the form of a text-based dialogue after starting a persuasion dialogue. According to the persuasion dialogue protocol described in Chapter 3, the human then has the option of challenging, agreeing, or disagreeing with the robot’s agenda, as shown in Figure 5.13. If the human challenges the robot’s agenda, the robot provides the evidence behind its proposed agenda. If the human agrees, the robot executes its own agenda; otherwise, the robot goes with the
human’s agenda.

- **Challenge Dialogue Panel:** The Challenge Dialogue panel is available to enable a \textit{challenge}(b) dialogue move from the human collaborator during all three argumentation-based dialogue opportunities to decide “where to search,” “how to get there,” or “what is found there.” This panel allows the human collaborator to challenge the robot during any of the argumentation-based dialogues (i.e., information-seeking, inquiry, or persuasion dialogue). Figure 5.14 shows a challenge dialogue panel for an information-seeking dialogue from the human collaborator to the robot during the “where to search” discussion.

![Figure 5.14: ArgHRI System Goal Challenge Window](image)

- **Deciding in the “what is found there” Dialogue Panel:**

  As per our modified Treasure Hunt Game in Section 4.3, the robot performs a \textit{sensor-sweep} task and captures five different images to share with the human-collaborator after reaching
a room. The ArgHRI system did not direct the robot to capture live pictures after reaching a room but used stock pictures of the assigned treasure set that were taken and saved earlier to prevent possible experimental failure due to robot camera failure. The interface module generates a “what is found there” dialogue panel where the human can discuss whether any treasures have been found in those images. The “what is found there” dialogue panel is identical in terms of the dialogue contents shown in Figure 5.16 but operates differently during minimal dialogue and full dialogue.

In minimal-dialogue mode, the robot does not know anything about the identity of the treasure. Thus the robot is incapable of inquiring of the human or “challenging” the human. If the human collaborator chooses the “I don’t know” option, then the Game Master simply deducts points for not being able to identify treasure.

In full-dialogue mode, however, the robot knows only the color information of an image, but it does not know how to identify a treasure. Therefore, the robot relies on the human collaborator to analyze the five images to identify if there is any treasure in the room. The full-dialogue mode provides an opportunity for collaboration between the robot and the human to discuss the identity of the treasure (if any). By default, the robot in full-dialogue mode invokes an information-seeking dialogue with the human collaborator, assuming that the human collaborator knows if there is a treasure in the images. If the human participant chooses “I don’t know,” an inquiry dialogue is triggered. The interface module generates a challenge dialogue panel for both the robot and the human collaborator, if needed. A sample “what is found there” dialogue panel to discuss the identity of a treasure is shown in Figure 5.15. The panel is context sensitive and only appears after the robot visits a room and shares the image.
5.3.5 Critique of User Interface

The Human-Robot Interface for the ArgHRI system is further examined below by following a modified version of Scholtz’s six high-level evaluation guidelines [Yanco et al., 2004]:

- Is sufficient status and robot location information available so that the operator knows the robot is operating correctly?

The robot location and its movement in the experimental environment is simulated on the map panel of the ArgHRI User Interface, as shown in Figure 5.5. The robot’s simulated health information appears in the game status panel shown in Figure 5.7.
• *Is the information coming from the robots presented in a manner that minimizes operator memory load, including the amount of information fusion that needs to be performed in the operators head?*

There are only two kinds of relevant information required, identified and provided by the robot in our THG: robot location and images from the robot after a robot visits a room. As shown in Figure 5.8, the map panel (A) updates the robot’s location as it travels, and the image panel (B) displays images from the robot for the one room that appears after the robot arrives at the room. In addition, the *full-dialogue* mode may further reduce memory load and increase information, by enabling argumentation-based dialogue for “where to search,” “how to get there,” and “what is found there” decisions.

• *Are the means of interaction provided by the interface efficient and effective for the human and the robot (e.g., are shortcuts provided for the human)?*

As shown in Figure 5.8, the ArgHRI interface is divided into five different zones based on the information necessary for interaction in the THG. The upper left zone presents the robot information in the map panel (A), the lower left zone displays the 5 images in the image panel (B). The upper right zone and lower right zone provides a dialogue history and dialogue panel to the human collaborator to engage in a dialogue with the robot. The bottom zone includes game related information using the game status panel (E), which includes the game score, the robot’s simulated health, and the number of found treasures. The human collaborator can only interact with the image panel (B) and dialogue panel (D).

In the ArgHRI System, the robot is capable of autonomously visiting all rooms in the THG based on an abstract plan, as detailed in Section 5.2.3. And the robot’s movement information is provided to the human collaborator visually in a 2D movement. The 2D movement on a map is more reliable and requires less overload on a system than a 3D interface or video feed since it requires less robot data [Nielsen and Goodrich, 2006]. Only the current images from the room the Robot has just visited are available to the robot (see Figure 5.6).
• *Does the interface support the operator directing the actions of more than one robot simultaneously?*

The interface support for operating multiple robots is not applicable since the ArgHRI interface is currently designed to support only interaction between one human and one robot. It is, however, possible to extend the ArgHRI interface to support multiple robots using the HRTeam’s multi-robot team framework.

• *Will the interface design allow for adding more sensors and more autonomy?*

The ArgHRI interface design takes a minimalist approach by providing streamlined information, as shown in Figure 5.8, leaving sufficient interface real-estate available for incorporating new information from new sensors or even operate multiple robots.

Table 5.2 evaluates the ArgHRI User Interface following design guidelines for results from three years of studying human-robot interaction in the context of the AAAI Robot Rescue Competition by Yanco and Dury [Yanco and Drury, 2007].

<table>
<thead>
<tr>
<th>USAR Guideline</th>
<th>ArgHRI User Interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>available map?</td>
<td>yes</td>
</tr>
<tr>
<td>single monitor for the interface?</td>
<td>yes</td>
</tr>
<tr>
<td>larger video/map windows to assist in completing the task?</td>
<td>yes</td>
</tr>
<tr>
<td>window occlusion hinders operation?</td>
<td>no</td>
</tr>
<tr>
<td>when multiple robots available, use one to view another?</td>
<td>not applicable</td>
</tr>
<tr>
<td>design for the intended user, not the developer?</td>
<td>use keyboard control</td>
</tr>
</tbody>
</table>

Table 5.2: Evaluation of ArgHRI Interface following USAR Guidelines
5.4 Software Development

The Human-Robot Interface for the ArgHRI system was developed in two phases, ArgHRI software version 1.0 (v1.0) and ArgHRI software version 2.0 (v2.0). Significant differences between v1.0 and v2.0 are discussed below:

- The initial version v1.0 of the ArgHRI software was deployed in preliminary user studies discussed in Chapter 6.

- The final version v2.0 of the ArgHRI 2.0 software incorporates a dialogue framework for inquiry dialogue and information-seeking dialogues, and persuasion dialogue whereas the ArgHRI v1.0 software supports only persuasion dialogue.

- The ArgHRI v2.0 employed ArgTrust v2.0, a more recent version, as its argumentation engine instead of earlier version of ArgTrust v1.0, which was used in the ArgHRI v1.0.
• The User Interface of the ArgHRI v1.0 shown in Figure (A) 5.18 was initially deployed as a prototype for the preliminary studies discussed in Chapter 6.

As shown in Figure 5.18 (B), the User Interface of ArgHRI v2.0 was completely redesigned, adopting the design principles and guidelines discussed in Section 5.3. Major changes from ArgHRI v1.0 User Interface (UI) to ArgHRI v2.0 User Interface (UI) are shown in Figure 5.18 and briefly described below:

• Five different areas have been identified for ArgHRI software, as shown in Figure 5.8, to make the interface user friendly and intuitive. Unlike the ArgHRI v1.0 UI, ArgHRI v2.0 UI logically divides the interface horizontally in two major regions. The left regions of ArgHRI v2.0 UI include the map panel (Figure 5.8 in the upper left corner (A)) and panels to display and select robot images in the lower left corner (Figure 5.8 (B)) to support human situational awareness. The right region of ArgHRI v2.0 includes the dialogue history panel (Figure 5.8 (C)) and the dialogue panel (Figure 5.8 (D)), which is dedicated to dialogue support.

• The game status panel (Figure 5.8 (E)) was moved from the upper left region of ArgHRI v1.0 to the bottom panel of ArgHRI v2.0.
Appendix C provides a demonstration of the ArgHRI System (ArgHRI 2.0) usage during Final User Study for both peer and supervisory interaction.
Chapter 6

Preliminary User Studies

The overall thesis aims to answer the following two research questions:

- **Research Question:** Does adding peer interaction enabled through argumentation-based dialogue to an HRI system improve system performance during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?

- **Research Question:** Does adding peer interaction enabled through argumentation-based dialogue to an HRI system improve user experience during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?

<table>
<thead>
<tr>
<th>which study</th>
<th>number of users</th>
<th>user level</th>
<th>feedback method</th>
<th>robot form</th>
<th>dialogue (s) type(s)</th>
<th>evaluation type</th>
<th>software versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>pilot study A (formative) (informal expert evaluation)</td>
<td>3</td>
<td>expert</td>
<td>interview</td>
<td>simulation (2), physical (1)</td>
<td>persuasion</td>
<td>subjective</td>
<td>ArgHRI System 1.0</td>
</tr>
<tr>
<td>pilot study B (formative) (novices)</td>
<td>6</td>
<td>novice</td>
<td>surveys</td>
<td>simulation (0), physical (6)</td>
<td>persuasion</td>
<td>subjective</td>
<td>ArgHRI System 1.0</td>
</tr>
<tr>
<td>user study 1 (formative)</td>
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<td>novice</td>
<td>surveys</td>
<td>simulation (20), physical (19)</td>
<td>persuasion</td>
<td>subjective</td>
<td>ArgHRI System 1.0</td>
</tr>
<tr>
<td>user study 2 (summative)</td>
<td>60</td>
<td>novice</td>
<td>surveys</td>
<td>simulation (33), physical (27)</td>
<td>persuasion, inquiry, information-seeking</td>
<td>subjective, objective</td>
<td>ArgHRI System 2.0</td>
</tr>
</tbody>
</table>

Table 6.1: A Summary of all User Studies with 108 human participants
The research presented in this thesis employs an argumentation-based interactive human-robot system with full dialogue to compare the effect of full versus minimal dialogue on system performance and user experience during human-robot collaboration during a game in our experimental Treasure Hunt Game domain, described in Chapter 4.3. The experiment was designed to be completed within an hour. All human participants were exposed to the following two experimental conditions in all four user studies as detailed in Chapter 4:

A. a minimal-dialogue mode **without argumentation-based dialogue**; in which the human provided supervisory commands to the robot and the robot obeyed; and

B. a full-dialogue mode **with argumentation-based dialogue** in which the human and robot conversed about what the robot should do and reached agreement before the robot took any actions.

Four different user studies were conducted involving a total of 108 human participants. The studies investigated our research questions and are summarized in Table 6.1:

- **formative experiments:**
  - a pilot study A (physical = 1 and simulation = 2) and a pilot study B (physical = 6) details in Section 6.1.
  - user study 1 (physical = 19 and simulation = 20) details in Section 6.2.

- **summative experiments:**
  - **user study 2** (physical = 27 and simulation = 33) details in Chapter 7.
6.1 Pilot Study

To evaluate and review the effectiveness of our work, we conducted a pilot study during Spring 2013 to achieve two goals. The first goal was to investigate whether an interactive, full human-robot dialogue had a positive or negative impact on user experience compared to minimal dialogue during human-robot collaboration. The second goal was to investigate which concepts could be conveyed within a dialogue that used an argumentation-based framework.

The pilot study A was conducted with expert users followed by the pilot study B with novice users. The expert users were developers of ArgTrust Engine or HRTeam software which are both integrated to the ArgHRI System developed for this research. Novice users were those who lacked familiarity with the ArgHRI software development. The other major distinction between the two groups was that the expert user studies used a simulated (virtual) robot and a physical robot, whereas the pilot study used only a physical robot in a physical arena. The pilot study version of the ArgHRI software 1.0 was designed to support only persuasion dialogue for this pilot study. None of the participants were paid for the pilot study.

6.1.1 Pilot Study A:

The primary reason for conducting the expert user study was to discover any immediate shortcomings of the system before the pilot study. Three expert users from the lab evaluated the system using the ArgHRI simulation environment. Each of them spent on average an hour evaluating the system. Feedback was provided in the form of an informal interview.

The first expert user was familiar with the ArgTrust engine and had some familiarity with robotics. We began with a short demonstration of the ArgHRI system using simulated robot and then continued with three Treasure Hunt Game scenarios for each mode. She was asked to first evaluate the minimal-dialogue mode and then the full-dialogue mode. Based on these experimental runs, we realized that each simulation took too long to execute. The expert user came to appreciate the system fully after a single run in full-dialogue mode. During the run, the user had a conflict.
with the robot’s plan, but since the robot suggested a more efficient path, the expert user was happy
to go along with the robot’s plan.

The second expert user had experience with both robotics and the ArgTrust engine. We also
began with a short demonstration of the system using simulated robot and continued with only two
Treasure Hunt Game scenarios for each mode. The second expert user found the scenario to be
simple and thought that the dialogue should be more plausible for complex, dynamic scenarios.
Even so, he found the full-dialogue mode more useful than the minimal-dialogue mode since it
gave more feedback.

The third expert user was familiar with robotics and the HRTeam system. As with the first two
expert users, we started with a demo of the system and then conducted two different Treasure Hunt
Game scenarios. The session with the third expert user employed a physical robot system rather
than the virtual robot that was used for the first two expert users. In dialogue mode, the third expert
user initially made a mistake and chose an inefficient path for the robot. Similar to the first expert
user, this user found the conflict resolution in the planning dialogue panel helpful. On the whole,
the third expert user found the full-dialogue mode more useful than the minimal-dialogue mode.

In general, the expert users’ feedback reinforced our hypothesis that the full-dialogue mode
would be perceived to be useful. Despite their feedback that a more complex scenario would
highlight the usefulness even more, we decided to proceed with the same simple scenario for the
pilot study. Our reasoning was that these experiments were meant to prove the overall usefulness of
the framework and prototype, whereas a complex environment might introduce other complexities
irrelevant to our fundamental research questions.

Based on the expert feedback, we made the following changes before our pilot study:

- Interface improvements were incorporated in our next set of experiments. For example, we
  changed the position of the “continue” button that becomes visible after each scenario is
  completed. This simple interface change made the pilot study more fluid.

- Instead of having users complete an online survey before and after a run using each mode,
we decided to only give one pre-survey, one mid-course survey after the minimal-dialogue mode run, and one final survey after full-dialogue mode run. This gave sufficient data points to capture each user’s experience of the system.

- Finally, based on the success with the third expert user, we decided to run the pilot study using physical robots.

6.1.2 Pilot Study B:

As we mentioned in the previous section, we decided to run the pilot study using physical robots since they provided a more compelling interaction with the ArgHRI system. Figure 6.1 shows the ArgHRI User Interface from the ArgHRI System 1.0 employed during pilot study.

**Experimental Setup:**

One robot was placed in the physical arena. The human participant, who was situated in a different room from the robot, used the dialogue manager to interface with the robot. During the demonstration of the system, participants were reminded about the robot’s limited “health” (think of it as battery power), which runs out as the robot travels. In addition, we explained that incorporated in the Treasure Hunt Game scenario is a scoring system: When a robot searches a room, the human participant gains 400 points if the robot finds a treasure, but loses 150 points, if it does not find one. The final score is based on the number of treasures the human-robot team finds combined with the robot’s remaining health. We made sure to point out that because of limited energy the robot may not be able to travel to all rooms. A sample game instruction provided to each human participant at the beginning of the experiment is included in Appendix B.

**Experimental Procedure:**

Each session involved the following procedure. The human participant was first given the purpose and the procedure of the experiment and asked to review a consent form. Participants were told
that they could leave and quit the experiment at any time. Participants were then brought into the experiment room and given a laptop to communicate with the robot remotely. This is important to note, since the human collaborators were situated in a different room and could not see the physical robot or the arena during the experimental runs. Knowledge of the arena was provided solely by the robot. After the participant was seated at the table with the laptop, the experimenter provided more detailed information on the experimental task. Participants then provided basic demographic information followed by a pre-survey for the minimal-dialogue mode. Following the completion of the minimal-dialogue mode portion of the experiment, the participant filled out a mid-course survey. Each participant then interacted with the robot in full-dialogue mode. Participants filled out a post-survey questionnaire at the end of the full-dialogue mode interaction.

The pilot was designed to support only persuasion dialogue. Inquiry and information-seeking dialogues were tested in my final User Study 2 described in Chapter 7.

Only the participant and the experimenter were present in the room during the experiment. Participants were not paid for this study.

Figure 6.1: ArgHRI Execution Window from Pilot and User Study 1
6.1.3 Data Collection and Analysis:

The pilot study participants consisted of six undergraduate research fellows who all had some familiarity with robotics but were not familiar with the software development. We asked five questions on the survey about collaboration, trust, dialogue, performance and effort in the context of human-robot collaboration. A screen-shot of the survey can be seen in Figure 6.2.

![Survey](image)

Figure 6.2: Survey

The pre-survey questions investigated participants’ perceptions of the following five topics at the three points in the session: (1) before minimal dialogue was initiated, (2) in the period between minimal- and full-dialogue modes (i.e., the mid-course survey), and (3) after full-dialogue mode.
completion (i.e., the post-survey):

- a **collaboration** question investigated if a robot collaborating with a human during peer interaction using full-dialogue mode would be a more reliable robot collaborator than a robot using minimal-dialogue mode;

- a **trust** question investigated if a robot collaborating with a human during peer interaction using full-dialogue mode would increase human’s level the trust level of a human collaborator more than a robot using minimal-dialogue mode;

- a **dialogue** question investigated if a robot collaborating with a human during peer interaction using full-dialogue mode would overwhelm human-robot communication more than a robot using minimal-dialogue mode;

- a **performance** question investigated if a robot collaborating with a human during peer interaction using full-dialogue mode would improve performance more than a robot using minimal-dialogue mode; and

- an **effort** question investigated if a robot collaborating with a human during peer interaction using full-dialogue mode would reduce the human collaborator’s effort more than a robot using minimal-dialogue mode.

Each survey used sliding Likert scales (20-point) and was administered online as part of the ArgHRI system.

Survey results are shown numerically in Table 6.2 and graphically in Figure 6.3. All participants favored full-dialogue over minimal-dialogue mode. For each topic covered in the surveys, positive changes were recorded for full-dialogue mode as compared to minimal dialogue mode.

These are illustrated in Table 6.2 [Azhar et al., 2013b]. The largest positive increase during full-dialogue mode was in the collaboration (i.e., 24.58%) followed by dialogue (i.e., 22.79%). The participants also found the robot more trustworthy in full-dialogue compared to minimum-dialogue
mode. The participants also found the robot more trustworthy in full dialogue mode compared to minimum dialogue.

<table>
<thead>
<tr>
<th></th>
<th>pre</th>
<th>mid</th>
<th>post</th>
<th>change</th>
</tr>
</thead>
<tbody>
<tr>
<td>collaboration</td>
<td>13.67</td>
<td>16.17</td>
<td><strong>18.33</strong></td>
<td>4.67 (<strong>24.58%</strong>)</td>
</tr>
<tr>
<td>trust</td>
<td>14.50</td>
<td>15.67</td>
<td><strong>16.17</strong></td>
<td>1.67 (8.79%)</td>
</tr>
<tr>
<td>dialogue</td>
<td>11.83</td>
<td>15.17</td>
<td><strong>16.17</strong></td>
<td>4.33 (<strong>22.79%</strong>)</td>
</tr>
<tr>
<td>performance</td>
<td>7.83</td>
<td>7.00</td>
<td><strong>8.50</strong></td>
<td>0.67 (3.53%)</td>
</tr>
<tr>
<td>effort</td>
<td>14.17</td>
<td>14.33</td>
<td><strong>14.50</strong></td>
<td>0.33 (1.74%)</td>
</tr>
</tbody>
</table>

Table 6.2: Average survey results across 6 participants from pilot study [Azhar et al., 2013b].

The pilot study presented in the research for this thesis suggested that compared to robots with minimal-dialogue capabilities the full-dialogue mode implemented in the ArgHRI framework using argumentation-based dialogue improved collaborative communication.

### 6.2 User Study 1

During Fall 2013, we conducted a large-scale evaluation incorporating lessons learned from the pilot study described in Section 6.1 using the same THG scenarios. Our User Study 1 investigated whether adding full-dialogue employing persuasion dialogue to an HRI system improved user experience during a simple collaborative task compared to an HRI system that did not use dialogue interaction. Our goal in the User Study 1 was to verify the user experience results from our earlier pilot study. In addition, we also investigated the characteristics of a collaborative complex task according to the human collaborator. The data collected from the User Study 1 aided us in designing the large-scale final and User Study 2 detailed in Chapter 7, which investigated whether adding full dialogue improves both system performance and user experience.
6.2.1 Experimental Procedure:

We first discuss the details of our User Study 1 identifying the differences from the earlier pilot study.

- **Human Participants:** Our large-scale evaluation included 39 undergraduate and graduate students. Our pilot study involved only 9 participants. We conducted our user study both in the physical experimental setup and simulated experimental setup.
  
  - **19** volunteers participated in the experiments with a *physical robot*. One of the participants was female and the rest were male.
  
  - **20** volunteers participated in the experiments with a *virtual robot*. Two of the participants were female and the rest were male.

The volunteers who participated in the live experiments with physical robots did not participate in the simulated experiments, and vice versa. None of the participants were paid for the User Study 1.

- **Experimental Environment:** We employed the Treasure Hunt Game domain for our experiment as we did in our earlier pilot study. There were between 1-4 treasures hidden in the map, which was comprised of six rooms. The participant’s goal was to collaborate with a robot to find two to four treasures that were randomly placed in the map before the experiments began.

  The *map* is that of the arena constructed in the Agents Robotics Lab at Brooklyn College, City University of New York, room 233 Roosevelt Hall. A drawing of the arena is shown in Figure 6.4. The map is the same for all THG rounds.

  **Experimental Domain:** We conducted our experiments both in physical setup and simulated setup.
• **Physical Experiment:** We conducted the experiments in both physical and simulated setups during the User Study 1.

  – Physical Experiment: The physical experiment was conducted using a physical robot in the Agents Robotics Lab in Brooklyn College.

  – Each trial of the experiment involved the procedures for physical experiment detailed in Chapter 6.1.

Each participant took about 30 minutes on average to complete the study, including filling out all surveys and a brief one-on-one post-experiment interview. Only the participant and the experimenter were present in the room during the experiment.

The physical experiment is conducted using a physical robot in our agents lab in Brooklyn College.

Each trial of the experiment involves the procedures for physical experiment detailed in Chapter 6.1.

• **Simulated Experiment:** Each participant was given a laptop to communicate with the simulated robot. The simulation experiment lacked the physical experimental setup, and the collaborator was not required to be in the physical lab. The rest of the procedure was the same as the physical experiment. The experiment, however, took on average 40 minutes during the study.

6.2.2 **Data Collection and Analysis:**

We collected subjective measures for the User Study 1, using data from the same three surveys: the pre-, mid-course, and post-experiment surveys. The same five questions from the pilot study were asked about collaboration, trust, dialogue, performance, and effort in the context of human-robot collaboration. In the pre-experiment survey, we also collected demographic data.
Each survey was administered on paper, as part of the ArgHRI system. The survey utilized a 5-point Likert scale (1-5), where 1 meant “strongly disagree,” and 5 meant “strongly agree.”

For all five topics covered in the surveys, positive changes were recorded for full-dialogue mode as compared to the minimal-dialogue mode. Survey results of positive and negative changes from the experiments using simulated robot are shown in Table 6.3 and the experiments using physical robots are shown in Table 6.4. The changes are highlighted in the rightmost columns in Table 6.3 and Table 6.4.

During the simulation experiment, which used a virtual robot, the full-dialogue mode Likert scale score that measured the impact of Dialogue was higher by 22.00% over the minimal-dialogue score. For the full-dialogue mode score that measured Trust, there was a 16.00% higher score over the minimal-dialogue mode. The participants also found the robot to be more collaborative in full-dialogue mode than in minimum dialogue (i.e., there was an increase of Likert scale scores of 10.00%). During the live experiment using the physical robot, the largest difference between full-dialogue and minimal-dialogue mode occurred for the topic of Dialogue (12.63%) followed by Trust (9.47%). The participants also found the robot to be more collaborative in full-dialogue than in minimal-dialogue mode (8.43%). The Effort topic showed a decrease in full-dialogue mode Likert scale scores of 4.00% in the simulation experiment and a small increase of 1.00% during the live experiment for Effort during the simulation experiment that suggests adding dialogue reduced, or at least did not increase, the human collaborator’s effort significantly during human-robot collaboration.

<table>
<thead>
<tr>
<th></th>
<th>pre</th>
<th>mid</th>
<th>post</th>
<th>(post-pre)</th>
<th>(mid-pre)</th>
<th>(post-mid)</th>
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</thead>
<tbody>
<tr>
<td>collaboration</td>
<td>3.85 (0.99)</td>
<td>4.25 (1.07)</td>
<td>4.35 (0.99)</td>
<td>0.50 (10.00%)</td>
<td>0.40 (8.00%)</td>
<td>0.10 (2.00%)</td>
</tr>
<tr>
<td>trust</td>
<td>3.50 (1.10)</td>
<td>4.00 (0.86)</td>
<td>4.30 (0.92)</td>
<td>0.80 (16.00%)</td>
<td>0.50 (10%)</td>
<td>0.30 (6.00%)</td>
</tr>
<tr>
<td>dialogue</td>
<td>2.65 (0.99)</td>
<td>3.65 (1.14)</td>
<td>3.75 (1.16)</td>
<td>1.10 (22.00%)</td>
<td>1.00 (20.00%)</td>
<td>0.10 (2.00%)</td>
</tr>
<tr>
<td>performance</td>
<td>3.00 (0.92)</td>
<td>2.95 (1.05)</td>
<td>3.30 (1.13)</td>
<td>0.30 (6.00%)</td>
<td>-0.05 (-1.00%)</td>
<td>0.35 (7.00%)</td>
</tr>
<tr>
<td>effort</td>
<td>2.90 (1.07)</td>
<td>2.90 (1.12)</td>
<td>2.70 (1.26)</td>
<td>-0.20 (-4.00%)</td>
<td>0.00 (0.00%)</td>
<td>-0.11 (-2.11%)</td>
</tr>
</tbody>
</table>

Table 6.3: Average survey results across 20 participants from simulation experiments using virtual robot from User Study 1.

In addition, we conducted post-experiment interviews and asked the following three questions...
Table 6.4: Average survey results across 19 participants from live experiments using physical robot from User Study 1.

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<th>(post-pre)</th>
<th>(mid-pre)</th>
<th>(post-mid)</th>
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</thead>
<tbody>
<tr>
<td>collaboration</td>
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<td>4.05 (0.78)</td>
<td>4.21 (0.71)</td>
<td>0.42 (8.42%)</td>
<td>0.26 (5.26%)</td>
<td>0.16 (3.16%)</td>
</tr>
<tr>
<td>trust</td>
<td>3.53 (0.77)</td>
<td>3.79 (0.71)</td>
<td>4.00 (0.67)</td>
<td>0.47 (9.47%)</td>
<td>0.26 (5.26%)</td>
<td>0.21 (4.21%)</td>
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<tr>
<td>dialogue</td>
<td>3.05 (1.08)</td>
<td>3.32 (1.20)</td>
<td>3.68 (1.00)</td>
<td>0.63 (12.63%)</td>
<td>0.26 (5.25%)</td>
<td>0.37 (7.37%)</td>
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<tr>
<td>performance</td>
<td>3.53 (0.90)</td>
<td>3.32 (1.00)</td>
<td>3.63 (1.01)</td>
<td>0.11 (2.11%)</td>
<td>-0.21 (-4.21%)</td>
<td>0.32 (6.32%)</td>
</tr>
<tr>
<td>effort</td>
<td>3.11 (1.05)</td>
<td>3.26 (0.99)</td>
<td>3.16 (1.01)</td>
<td>0.05 (1.05%)</td>
<td>0.16 (3.16%)</td>
<td>-0.11 (-2.11%)</td>
</tr>
</tbody>
</table>

related to the User Study 1:

- Given minimal-dialogue (first experimental mode) and full-dialogue mode (second experimental mode), which mode would you choose while collaborating with a robot?
  - 15 out of 19 participants (78.94%) favored the full-dialogue mode over minimal-dialogue mode during experiments with a physical robot.
  - 13 out of 20 participants (65%) favored the full-dialogue mode over minimal-dialogue mode during experiments with a simulated robot.

- Did you find the given task simple or complex?
  - 37 out of the 39 participants (94.87%) considered the given collaborative task to be simple.

- Given a complex task, would you prefer minimal dialogue or full dialogue?
  - All 39 participants (100%) favored full-dialogue mode during complex tasks.

6.3 Discussion

Our User Study 1 concluded that full-dialogue mode can improve user experience even during a simple task. This was similar to the results from the Pilot Study. The User Study 1 did not control for the order effect. All human participants were exposed to minimal-dialogue mode first
followed by full-dialogue mode. We kept the same survey questions. Yet user satisfaction with collaboration, trust, dialogue, performance, and effort increased steadily between minimal and full dialogue.

Regardless of the simplicity of the task, as well as lack of conflicts during full-dialogue mode, the post-experiment interview data suggested that full dialogue improves the user’s experience by providing more information and feedback. Interestingly, given the simple task, 71% (28 out of 39) participants favored full-dialogue mode over minimal-dialogue mode during both physical and simulated experiments. All 39 participants preferred the full-dialogue mode during complex tasks. Our user study suggests that there may be significant increase in subjective metrics scores between minimal-dialogue and full-dialogue for more complex collaborative tasks as well as more opportunities for collaborative decision-making.
Figure 6.3: Graphs of average survey results across 6 participants from pilot study. Each line represents the responses from one participant. The y-axis contains possible ratings, from 1 (worse) to 20 (better). The x-axis contains three points: the leftmost point aligns with the pre-survey, followed by the mid survey and ending with the post-survey on the right.
Figure 6.4: Experimental arena
Figure 6.5: Box-and-whiskers plots of results from User Study 1. Thick red horizontal bars indicate the median. Boxes extend from 25th percentile to 75th percentile. Whiskers extend from minimum value to maximum. Y-axis values correspond to Likert-scale answers provided by participants in user study, ranging from $1 = \text{strongly disagree}$ to $5 = \text{strongly agree}$. Blue boxes correspond to simulated robot experimental condition (20 participants), and green boxes correspond to live robot experimental condition (19 participants).
Figure 6.6: Statistical plots of results from User Study 1. Thick magenta horizontal bars indicate the mean. Boxes extend from 2 standard deviations below the mean to 2 standard deviations above the mean. Y-axis values correspond to Likert-scale answers provided by participants in user study, ranging from $1 = \text{strongly disagree}$ to $5 = \text{strongly agree}$. Blue boxes correspond to simulated robot experimental condition (20 participants), and green boxes correspond to live robot experimental condition (19 participants).
Chapter 7

Final User Study Results

In my User Study 2, I employed simple tasks that utilized complex dialogues with information-seeking, inquiry, and persuasion dialogues that then incorporated lessons learned from the preliminary user studies. Chapter 4.3 discusses our comprehensive within-subject experimental design for the final user study.

All experiments were conducted using a treasure hunt game (THG) environment. Three types of argumentation-based dialogues (i.e., persuasion, information-seeking and inquiry) were employed using full dialogue as detailed in Chapter 4.2.

The human-robot team played the THG under two experimental conditions detailed in Section 4.4:

- using a minimal-dialogue mode in which the human commanded the robot and the robot obeyed during supervisory interaction; and

- using a full-dialogue mode in which the human and robot conversed about what the robot should do and reached agreement before the robot took any actions during peer interaction.

Half the human participants see minimal dialogue mode first and then full dialogue mode, and the other half of the human participants see full dialogue mode first and then minimal dialogue mode. Section, 7.2, details data collection during the experiments and data analysis methods. The
final Section, 7.3.2, 7.3.3, and 7.4 detail the analysis of objective measures, subjective measures and the impacts of argumentation-based full dialogue during human-robot collaboration respectively from my final user study. Half the recruited human participants participated with physical robots and half with simulated robots, which is a common practice in the robotics community [Harris and Rudnicky, 2007].

As mentioned earlier, three types of argumentation-based dialogues (i.e., persuasion, information-seeking and inquiry) were employed using full dialogue. These three dialogues cover the various combinations of shared beliefs between a human and robot collaborator as described in Chapter 4.

### 7.1 Experimental Protocol:

In final User Study 2 half the human participants interacted with the minimal-dialogue mode first and then full-dialogue mode, and the other half of the human participants interacted first with the full dialogue mode and then the minimal-dialogue mode. To make the dialogue mode transparent to the human participants during the final user study, the experiment was presented to human participants as though it included two different robots.

“Mary,” the robot in minimal-dialogue mode, only obeyed commands given by the human subject acting in a supervisory role [Scholtz, 2003]. “Fiona,” the robot in full-dialogue mode, communicated with the human using structured argumentation-based dialogues in which the human and robot interacted with each other as peers and reached agreement about the robot’s actions in the THG arena before any actions were taken. Each human subject played a single game with Mary and with Fiona.

The sequence of each experiment will thus run like this:

- step 1: complete informed consent
- step 2: provide experimental instructions
- step 3: complete pre-survey
• step 4: complete first experiment (minimal dialogue mode or full dialogue mode)

• step 5: complete mid-survey

• step 6: complete second experiment (minimal dialogue mode or full dialogue mode that was not employed in step 4)

• step 7: complete post-survey

Table 7.1 has sample sequences of several experimental runs:

<table>
<thead>
<tr>
<th>user id</th>
<th>step 1</th>
<th>step 2</th>
<th>step 3</th>
<th>step 4</th>
<th>step 5</th>
<th>step 6</th>
<th>step 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>user 1, 5, ...</td>
<td>informed consent</td>
<td>experimental instructions</td>
<td>pre-survey</td>
<td>Robot Mary (minimal dialogue mode)</td>
<td>mid survey</td>
<td>Robot Fiona (full dialogue mode)</td>
<td>post-survey</td>
</tr>
<tr>
<td>user 2, 6, ...</td>
<td>informed consent</td>
<td>experimental instructions</td>
<td>pre-survey</td>
<td>Robot Fiona (full dialogue mode)</td>
<td>mid survey</td>
<td>Robot Mary (minimal dialogue mode)</td>
<td>post-survey</td>
</tr>
<tr>
<td>user 3, 7, ...</td>
<td>informed consent</td>
<td>experimental instructions</td>
<td>pre-survey</td>
<td>Robot Mary (minimal dialogue mode)</td>
<td>mid survey</td>
<td>Robot Fiona (full dialogue mode)</td>
<td>post-survey</td>
</tr>
<tr>
<td>user 4, 8, ...</td>
<td>informed consent</td>
<td>experimental instructions</td>
<td>pre-survey</td>
<td>Robot Fiona (full dialogue mode)</td>
<td>mid survey</td>
<td>Robot Mary (minimal dialogue mode)</td>
<td>post-survey</td>
</tr>
</tbody>
</table>

Table 7.1: User Study 2 Experimental Procedures

7.2 Data Collection:

Our dependent variables and independent variables are described below:

• dependent variables (DV): changes between pre-survey/objective data and after mid-survey/objective data, and changes between pre-survey/objective data and post-survey/objective data.

• independent variables (IV):
  
  – level of dialogue (within subject) [2(Level of Dialogue)]:
    
    A. minimal-dialogue mode without argumentation-based dialogue; and
    
    B. full-dialogue mode with argumentation-based dialogue.
Both subjective and objective measures were conducted on the following kinds of data for final user study:

- subjective measures were determined by analyzing a Likert-type scale pre-experiment survey, mid-course survey and post-experiment survey data. Survey questions can be found in the Appendix B. Each survey was administered on paper, as part of the ArgHRI system

- objective measures were determined by analyzing system data from HRTeam system and ArgHRI.

  - Deliberation time data were collected by the HRTeam system, that is to say the time that it took for the human and robot to reach agreement during the “where to go” and “how to go” discussions.

  - Execution time was collected by the HRTeam system. It was the time from when the robot began moving until the game was over.

  - ArgHRI GUI collected the following clickstream data during each dialogue mode for dialogue analysis. The analysis of this data is discussed in 7.4.

    * a log of when the human collaborator was in agreement with the robot during a full dialogue.

    * a log of when the human collaborator was in disagreement with the robot during a full dialogue.

    * a log of when the human collaborator challenged the robot during a full dialogue.

A repeated t-tests statistical method was employed to analyze parametric objective data. A Wilcoxon Signed-Rank Test, a nonparametric statistical method, was employed to analyze ordinal subjective data.
7.3 User Study 2 Analysis

The User Study 2 followed a within-subject design in which each human participant played treasure-hunt games with robot Mary and robot Fiona (see Section 4.3 for a fuller description).

7.3.1 Participants:

I recruited 63 human participants for the User Study 2, which was conducted during Fall 2014. The User Study 2 was the final user study that was conducted during Fall 2014. Thirty of sixty-three participants (48%) collaborated with physical robots in a laboratory and received monetary compensation ($10) for participating for an hour. Additional monetary compensation ($10) was given to those thirty participants for travel time and transportation fare. The remaining 33 participants (52%) collaborated with robots in a simulated version of the physical laboratory set-up and received monetary compensation ($10) for an hour of participation. The experiments in a physical laboratory environment needed longer time commitment and required the participant to make a trip to the agent lab at Brooklyn College. A simulated experimental environment was provided (and hence half the compensation) to those participants who wanted to participate in the experiment but were unavailable to visit the physical laboratory environment at Brooklyn College. Differences in monetary compensation for the physical and simulated experiments were explained to the participants during recruitment. Physical and simulation experiments were conducted simultaneously. Forty-four participants (22 in Physical and 22 in Simulation) were males (70%), and 19 participants (8 in physical and 11 in Simulation) were females (30%). Sixty-eight percents of the participants ranged in age from 18 to 24 while the remaining 32% participants were 25 to 39 years old. Participants included a doctoral student, an academic staff member, while the rest of the 97% participants were undergraduate students from the City University New York. Eighty-six percentage (86%) participants were frequent computer users. Fifty-nine percent (59%) had no prior experience with robots while 41.25% had interacted with robots before. Sixty-five percentage (65%) of those participants who interacted with a robot had less than one year of undergrad/grad robot experience.
Further details on collected demographic data are included in the Appendix D.

This section includes User Study 2 analysis of subjective and objective data from twenty-seven participants who collaborated with physical robots in a laboratory environment and thirty-three human participants who collaborated with a simulated robot. Note that both objective and subjective data from three human participants were omitted due to invalid objective data from unexpected robot failures during physical experiments.

This section details the objective measures (i.e., performance metrics) in Section 7.3.2, the subjective measures (i.e., the in-experiment survey data) in Section 7.3.3, and analysis of argumentation-based full-dialogue data in Section 7.4 to find the answers to the two research questions and evaluate how effective improving system performance and user experience through argumentation-based full-dialogue was.

7.3.2 Objective Analysis:

The objective analysis addresses my first research question, which I evaluated separately with physical and simulated robots:

- **Research Question:** Does adding peer interaction enabled through argumentation-based dialogue to an HRI system improve system performance during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?

In the remainder of this section, *peer interaction enabled through argumentation-based dialogue* is labeled as *full-dialogue*, and *minimal-dialogue* refers to dialogue that is conducted during supervisory interaction in which the robot follows human commands only.

System performance is measured using the following three performance metrics: (a) **deliberation time** (in seconds) is the amount of time a robot and human collaborator spend deciding what the robot should do. In our ArgHRI system, the deliberation time started at the time the robot
Figure 7.1: Physical Experiment \((n = 27)\): Total Distance Traveled

Figure 7.2: Physical Experiment \((n = 27)\): Total Execution Time
Figure 7.3: Simulation Experiment ($n = 33$): Total Distance Traveled

Figure 7.4: Simulation Experiment ($n = 33$): Total Execution Time
and the human collaborator began either minimal-dialogue or full-dialogue until the robot started executing a plan. (b) execution time (in seconds) is the amount of time a robot spends executing the plan formulated during the deliberation period. In our ArgHRI System, the execution time started at the time the robot began moving to execute the plan until the robot stopped moving. (c) distance travelled (in cm): It is the total distance that the robot travelled during the THG game. In our ArgHRI System, the distance travelled was the total path the robot travelled visiting all the rooms chosen during planning.

We propose the following hypotheses for physical-robot situation with respect to each performance metric mentioned above:

**H1a.** In the physical-robot situation, deliberation time for human-robot games will vary, less time for the minimal-dialogue robot Mary than for full-dialogue robot Fiona. This is because it will take more discussion time for the human and robot to reach agreement using our argumentation-based full-dialogue system than were the human simply to provide commands to the robot ($H_0 : F = M; H_A : F > M$);

**H2a.** In the physical-robot situation, execution time will be less for human-full-dialogue robot Fiona games than for human-minimal-dialogue robot Mary games because argumentation-based full-dialogue plans will be more efficient. The human and robot will combine abilities and reach agreement about the best plan ($H_0 : F = M; H_A : F < M$); and

**H3a.** In the physical-robot situation, distance travelled will be less for the human-full-dialogue robot Fiona games than for the human-minimal-dialogue robot Mary games for the same reason that execution time will be less ($H_0 : F = M; H_A : F < M$).

We propose the following hypotheses for simulated-robot situation with respect to each performance metric:

**H1b.** In the simulated-robot situation, deliberation time for human-robot games will vary, less time for the minimal-dialogue robot Mary than for full-dialogue robot Fiona. This is because
it will take more discussion time for the human and robot to reach agreement using our argumentation-based full-dialogue system than were the human simply to provide commands to the robot; \((H_0 : F = M; H_A : F > M)\);

H2b. In the simulated-robot situation, execution time will be less for human-full-dialogue robot Fiona games than for human-minimal-dialogue robot Mary games because argumentation-based full-dialogue plans will be more efficient. The human and robot will combine abilities and reach agreement about the best plan; \((H_0 : F = M; H_A : F < M)\); and

H3b. In the simulated-robot situation, distance travelled will be less for the human-full-dialogue robot Fiona games than for the human-minimal-dialogue robot Mary games for the same reason that execution time will be less \((H_0 : F = M; H_A : F < M)\).

A repeated measures (paired difference) \(t\)-test was performed to evaluate my hypotheses and analyze the significance of the performance metrics of parametric data for the minimal- and full-dialogue mode results. The objective results from physical experiments appear in Table 7.2 and the results of the simulation experiments appear in Table 7.3. For physical experiments the null hypothesis was rejected for all three tests related to performance \((df = 26, \alpha = .05)\). The null hypothesis was also rejected for all three tests related to performance for simulation experiments \((df = 32, \alpha = .05)\).

In terms of overall execution time measured in seconds, full-dialogue human-robot Fiona games were accomplished in less time than those using minimal-dialogue mode for both physical-robot and simulation-robot. On average, users took longer to deliberate (i.e., decide what to do) with Fiona but less time to execute the agreed-upon plan, which paid off in terms of distance travelled, because robot Mary travelled significantly farther than robot Fiona.
<table>
<thead>
<tr>
<th>H#</th>
<th>hypothesis</th>
<th>result</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a</td>
<td>deliberation time for human-robot games will vary, less time for the minimal-dialogue robot Mary than for full-dialogue robot Fiona.</td>
<td>H1a supported</td>
</tr>
<tr>
<td>H2a</td>
<td>execution time will be less for human full-dialogue robot Fiona games than for human min-dialogue robot Mary games.</td>
<td>H2a supported</td>
</tr>
<tr>
<td>H3a</td>
<td>distance travelled will be less for human full-dialogue robot Fiona games than for human min-dialogue robot Mary games.</td>
<td>H3a supported</td>
</tr>
</tbody>
</table>

Table 7.2: Summary of Hypotheses Results based on a statistical analysis of Repeated t-tests from Physical Experiments (number of participants=27) on Performance Metrics.

<table>
<thead>
<tr>
<th>H#</th>
<th>hypothesis</th>
<th>result</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1b</td>
<td>deliberation time for human-robot games will vary, less time for the minimal-dialogue robot Mary than for full-dialogue robot Fiona.</td>
<td>H1b supported</td>
</tr>
<tr>
<td>H2b</td>
<td>execution time will be less for human full-dialogue robot Fiona games than for human min-dialogue robot Mary games.</td>
<td>H2b supported</td>
</tr>
<tr>
<td>H3b</td>
<td>distance travelled will be less for human full-dialogue robot Fiona games than for human min-dialogue robot Mary games.</td>
<td>H3b supported</td>
</tr>
</tbody>
</table>

Table 7.3: Summary of Hypotheses Results based on a statistical analysis of Repeated t-tests from Simulation Experiments (number of participants=33) on Performance Metrics.
7.3.3 **Subjective Analysis:**

The subjective analysis addresses my second research question, which I evaluated separately with physical and simulated robots:

- **Research Question:** *Does adding peer interaction enabled through argumentation-based dialogue to an HRI system improve user experience during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?*

The remainder of this section *peer interaction enabled through argumentation-based dialogue* is labeled as *full-dialogue* mode and *minimal-dialogue* mode refers to dialogue during supervisory interaction where the robot just follows human’s commands as in Pilot Study and User Study 1. As per the experimental design, half the participants played THG games with robot Mary first, and the other half played with robot Fiona first. The in-experiment survey data were collected three times from each human collaborator during the experiment: “pre” (before the first game), “post-Mary” (after the game was played with robot Mary using minimal-dialogue mode), and “post-Fiona” (after the game was played with robot Fiona using full-dialogue mode). Each answer was given on a 7—point Likert scale instead of a 5—point Likert scale (as appeared in User Study 1 and the Pilot study) to capture more reliable data. I also revised multiple sub-questions to the survey for User Study 1 to cover four topics regarding the human perceptions of robot helpfulness, collaboration, trust, and efforts at interaction dialogue with robot Fiona. The interaction employed argumentation-based full dialogue. Multiple survey questions were used to obtain more reliable feedback from human participants. Identical question in multiple forms were asked to ensure that consistent answers were provided. In the subjective analysis, the answers are pooled and averaged. User Study 2 survey questions are listed in the Appendix B.

(a) robots helpfulness: how much the robot helps the human to complete the task successfully
(questions s1–s2),

(b) collaboration: how easy it is to collaborate with a robot (questions c1–c3),

(c) trust: how much the human trusts the robot (questions t1–t3), and

(d) effort of dialogue: how much the human were effected by dialogue (questions d1–d2).

The following hypotheses concern the second research question on the impact of full-dialogue collaboration with a physical robot:

H4a. In the physical-robot situation, the user-perception of the success of human-robot games will be more positive for full-dialogue robot Fiona than minimal-dialogue robot Mary;

H5a. In the physical-robot situation, the user-perception of ease of collaboration in human-robot games will be more positive for full-dialogue robot Fiona than for minimal-dialogue robot Mary;

H6a. In the physical-robot situation, the user-perception of levels of trust in human-robot games will be higher for full-dialogue robot Fiona than for minimal-dialogue robot Mary; and

H7a. In the physical-robot situation, the user-perception of the effort to engage in dialogue in human-robot games will be higher for full-dialogue robot Fiona than for minimal-dialogue robot Mary.

The following hypotheses concern the second research question on the impact of full-dialogue collaboration with a simulated robot:

H4b. In the simulated-robot situation, the user-perception of the success of human-robot games will be more positive for full-dialogue robot Fiona than minimal-dialogue robot Mary;

H5b. In the simulated-robot situation, user-perception of ease of collaboration in human-robot games will be more positive for full-dialogue robot Fiona than for minimal-dialogue robot Mary;
Table 7.4: In-experiment Survey Questions.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Question</th>
<th>Null Hypothesis</th>
<th>Alternative Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>H4a and H4b</td>
<td>I think that I can collaborate successfully with a robot in the treasure hunt game.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H4a and H4b</td>
<td>I think that I can be successful at the Treasure Hunt Game without a robot’s help.</td>
<td>$H_0: F = M$; $H_A: F &lt; M$</td>
<td></td>
</tr>
<tr>
<td>H5a and H5b</td>
<td>I think that collaborating with a robot will make my task easier than working on the task alone.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H5a and H5b</td>
<td>In general, I find it easier to work alone.</td>
<td>$H_0: F = M$; $H_A: F &lt; M$</td>
<td></td>
</tr>
<tr>
<td>H5a and H5b</td>
<td>I think that I can complete the task quickly while getting help from the robot.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H6a and H6b</td>
<td>I think that a robot can be a trustworthy collaborator.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H6a and H6b</td>
<td>I think that the robot will provide me with reliable information that will help me succeed in the task.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H6a and H6b</td>
<td>I trust the robot to catch something I miss while I am making my decision.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H7a and H7b</td>
<td>I don’t think that I have to expend a lot of effort to communicate with a robot.</td>
<td>$H_0: F = M$; $H_A: F &gt; M$</td>
<td></td>
</tr>
<tr>
<td>H7a and H7b</td>
<td>I think that discussing with the robot will slow me down to make the decision.</td>
<td>$H_0: F = M$; $H_A: F &lt; M$</td>
<td></td>
</tr>
</tbody>
</table>

H6b. In the simulated-robot situation, user-perception of *levels of trust* in human-robot games will be higher for full-dialogue robot Fiona than for minimal-dialogue robot Mary; and

H7b. In the simulated-robot situation, user-perception of the *effort to engage in dialogue* in human-robot games will be higher for full-dialogue robot Fiona than for minimal-dialogue robot Mary.

Table 7.4 lists the survey questions inspired by NASA-TLX [Hart and Staveland, 1988; Hart, 2006] with respect to each hypothesis for the subjective measures. We examine the differences in values between post-Mary and post-Fiona surveys and leave consideration of the pre-post analysis for future work 8.2.

This section reports on the results from a Wilcoxon Signed-Rank test of the subjective data from physical and simulation User Study 2 experiments. The nonparametric statistical method Wilcoxon Signed-Rank test is employed on pair-wise comparisons of ordinal data for *post-Mary* → *post-Fiona*. Multiple survey questions that relate to hypotheses are averaged before employing the Wilcoxon Signed-Rank test. For example, the scores from robot-helpfulness survey question 1
Table 7.5: Summary of Hypotheses Results from Subjective Analysis of Physical Experiments (number of human participants=27).

<table>
<thead>
<tr>
<th>H #</th>
<th>Hypothesis</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H4a</td>
<td><strong>robot-helpfulness:</strong> user-perception of the success of human-robot games will be more positive for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H4a not supported</strong></td>
</tr>
<tr>
<td>H5a</td>
<td><strong>ease of collaboration:</strong> user-perception of ease of collaboration in human-robot games will be more positive for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H5a supported</strong> (p = 0.0001)</td>
</tr>
<tr>
<td>H6a</td>
<td><strong>trust:</strong> user-perception of levels of trust in human-robot games will be higher for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H6a supported</strong> (p = 0.0001)</td>
</tr>
<tr>
<td>H7a</td>
<td><strong>effort of dialogue:</strong> user-perception of the effort to engage in dialogue in human-robot games will be higher for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H7a supported</strong> (p = 0.009)</td>
</tr>
</tbody>
</table>

(s1) and survey question 2 (s2) were averaged into a single (composite) helpfulness survey score for each human participant.

The results of the subjective measures obtained during User Study 2 were borne out by the Wilcoxon signed-rank test, as summarized in Table for physical (n = 27) and Table for simulation (n = 33) experiments. To summarize, the results of the subjective measures from the physical experiment showed that three hypotheses were supported (i.e., H5a, H6a, and H7a), and one was not supported (i.e., H4a). To summarize, the results of the subjective measures from the simulation experiments showed that three hypotheses for subjective measures were supported (i.e., H4b, H5b, and H6b), and one was not supported (i.e., H7b). The data clearly demonstrate that in both physical and simulation experiments, user expectations of interacting with the robots were closer to their experiences with full-dialogue robot Fiona than with their experiences with minimal-dialogue robot Mary.
<table>
<thead>
<tr>
<th>H #</th>
<th>Hypothesis</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H4b</td>
<td><strong>robot-helpfulness:</strong> user-perception of the success of human-robot games will be more positive for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H4b supported</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(p = 0.001)</td>
</tr>
<tr>
<td>H5b</td>
<td><strong>ease of collaboration:</strong> user-perception of ease of collaboration in human-robot games will be more positive for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H5b supported</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(p = 0.0002)</td>
</tr>
<tr>
<td>H6b</td>
<td><strong>trust:</strong> user-perception of levels of trust in human-robot games will be higher for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H6b supported</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(p = 0.0005)</td>
</tr>
<tr>
<td>H7b</td>
<td><strong>effort of dialogue:</strong> user-perception of the effort to engage in dialogue in human-robot games will be higher for full-dialogue robot Fiona than minimal-dialogue robot Mary.</td>
<td><strong>H7b not supported</strong></td>
</tr>
</tbody>
</table>

Table 7.6: Summary of Hypotheses Results from Subjective Analysis of Simulation Experiments (number of human participants=33).
7.4 Full-Dialogue Analysis:

As per the experimental design, human participants were exposed to two experimental conditions:

A. minimal-dialogue mode without argumentation-based dialogue; and

B. full-dialogue mode with argumentation-based dialogue.

Half the participants collaborated with robot Mary using minimal-dialogue mode first and then collaborated with robot Fiona using full-dialogue mode. The other half of the participants collaborated with robot Fiona using full-dialogue mode first and then collaborated with robot Mary using minimal-dialogue mode. My analysis of argumentation-based dialogues from User Study 2 is independent of the objective analysis detailed in Section 7.3.2 and the subjective measures detailed in 7.3.3. Dialogue data was collected by the ArgHRI System internally and was intact for all sixty-three participants. The argumentation-based dialogues recorded during User Study 2 full-dialogue mode are analyzed and presented in this section. They suggest opportunities for future research.

During User Study 2, robot Fiona engaged in full-dialogue mode with the human collaborator employing argumentation-based dialogue proposed in this thesis (see the Approaches and Methodology section). For each full-dialogue experimental mode, both robot Fiona and the human collaborator had three different opportunities during each treasure-hunt game to engage in full dialogue to discuss “where to search,” “how to get there,” and the “identity of the treasure” (as detailed in the Experimental Design section). There were 189 unique opportunities for both robot Fiona and its human collaborator to engage in a full dialogue employing argumentation-based dialogue. In addition, there were more than two different dialogue opportunities (based on the number of rooms the robot visited) for each experiment. Each decision was preceded by the belief setup required to trigger an argumentation-based dialogue. One of the three argumentation dialogues (information-seeking, inquiry, or persuasion dialogue) presented in this thesis was triggered, if the pre-conditions were met, except when the human collaborator and robot Fiona were in agreement as described in Table 4.3.
All human participants interacted with either a physical or simulated robot but not both. Physical and simulation experiments were conducted simultaneously during final user study. This section analyzes the following argumentation-dialogue data collected from human participants who participated in physical or simulation experiments during their collaboration with robot Fiona:

- number of times the human collaborator accepted robot Fiona’s argument for each dialogue
- number of times the human collaborator rejected robot Fiona’s argument for each dialogue
- number of times the human collaborator challenged robot Fiona
- number of times robot Fiona challenged the human collaborator
- number of times information-seeking dialogue occurred
- number of times inquiry dialogue occurred
- number of times persuasion dialogue occurred and ended in successful persuasion
- number of times each human collaborator said “I don’t know” and sought robot’s help, and
- number of times “no dialogue” occurred because robot Fiona and the human collaborator were in agreement.

In the physical-robot situation, there were 21 different argumentation-based dialogues (70%) triggered during the where to search discussion. The remainder (30%) were No Dialogue cases in which the human collaborators and the robot Fiona agreed and no dialogue was needed. The human collaborator challenged the robot Fiona in 15 of 21 of those argumentation-based dialogues (71%) and asked for evidence. In only two dialogues (10%) did the human collaborator disagree with the robot Fiona. In 19 dialogues (90%), “where to search” discussions ended in agreement.

In the simulated-robot situation, there were 27 different argumentation-based dialogues (82%) triggered during where to search discussions. The remainder (28%) were No Dialogue cases in
which the human collaborators and the robot Fiona agreed and no dialogue was needed. The human collaborator challenged the robot Fiona in 15 of 21 of those Argumentation-based dialogues (71%) and asked for evidence. In only two dialogues (10%) did the human collaborator disagree with the robot Fiona. In 19 dialogues (90%) “where to search” discussions ended in agreement.

A. Discuss “where to search?”

Robot Fiona and the human collaborator discussed the number of rooms that needed to be explored to find the maximum number of treasures in the shortest amount of time. Table 7.7 below summarizes the number of argumentation-based dialogues that occurred to discuss “where to search.” The dialogues were based on the information from the game master and belief inputs from the human participant.

<table>
<thead>
<tr>
<th></th>
<th>No Dialogue (Agreement)</th>
<th>%</th>
<th>ArgDialogue</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Experiments</td>
<td></td>
<td>9</td>
<td>21</td>
<td>70</td>
</tr>
<tr>
<td>Simulation Experiments</td>
<td></td>
<td>6</td>
<td>27</td>
<td>82</td>
</tr>
</tbody>
</table>

Table 7.7: Argumentation-based Dialogues triggered during where to search discussion

<table>
<thead>
<tr>
<th></th>
<th>ArgDial</th>
<th>Total%</th>
<th>Ch</th>
<th>ArgDial%</th>
<th>Acc</th>
<th>ArgDial%</th>
<th>Rej</th>
<th>ArgDial%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Experiments</td>
<td>21</td>
<td>70%</td>
<td>15</td>
<td>71%</td>
<td>19</td>
<td>90%</td>
<td>2</td>
<td>10%</td>
</tr>
<tr>
<td>Simulation Experiments</td>
<td>27</td>
<td>82%</td>
<td>16</td>
<td>59%</td>
<td>25</td>
<td>93%</td>
<td>2</td>
<td>7%</td>
</tr>
</tbody>
</table>

Table 7.8: Argumentation-based Dialogues triggered during where to search discussion where Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

B. Discuss “how to get there?” Robot Fiona and the human collaborator discussed the most efficient order of rooms that had to be explored to find the maximum number of treasures (i.e., a path through all the agreed-upon rooms) in the shortest amount of time. Table 7.9 and Table 7.10 below report the analysis of how to get there argumentation-based dialogues.

B. Discuss “how to get there?” Robot Fiona and the human collaborator discussed the most efficient order of rooms that had to be explored to find the maximum number of treasures (i.e., a path through all the agreed-upon rooms) in the shortest amount of time. Table 7.9 and Table 7.10 below report the analysis of how to get there argumentation-based dialogues.

C. Discuss “what is found there?” Robot Fiona and the human collaborator discussed the existence of treasure (if any) after visiting each rooms based on the images provided by the robot Fiona. Table 7.11 below summarizes the number of argumentation-based dialogues that occurred during the discussion of “what is found there”.

148
Table 7.9: Argumentation-based Dialogues triggered during how to get there discussion

<table>
<thead>
<tr>
<th></th>
<th>No Dialogue (Agreement)</th>
<th>%</th>
<th>ArgDialogue</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Experiments</td>
<td>12 40%</td>
<td></td>
<td>18 60%</td>
<td></td>
</tr>
<tr>
<td>Simulation Experiments</td>
<td>11 33%</td>
<td></td>
<td>22 67%</td>
<td></td>
</tr>
</tbody>
</table>

Table 7.10: Argumentation-based Dialogues triggered during how to get there discussion where Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

Analysis of individual argumentation-based dialogues:

- **No Dialogue** was required when the human collaborator and robot Fiona were in agreement.
  - In the physical-robot situation, robot Fiona and the human collaborators were in agreement about the number of rooms to explore on 9 (30%) occasions.
  - In the simulated-robot situation, robot Fiona and the human collaborators were in agreement about the number of rooms to explore on 6 (18%) occasions.
  - In the physical-robot situation, robot Fiona and the human collaborators were in agreement about the how the robot should travel the map to find the treasures on 12 (40%) occasions.
  - In the simulated-robot situation, robot Fiona and the human collaborators were in agreement about the how the robot should travel the map to find the treasures on 11 (33%) occasions.
  - There were always dialogue triggered during “what is found there” discussions in which the robot Fiona did not know how to identify a treasure.

- **Information-Seeking Dialogue**: In this scenario, the robot Fiona did not know “how many rooms to visit” and set the value for $b \in \Delta_R$ since it received no clue(s) from the game.
<table>
<thead>
<tr>
<th></th>
<th>Total ArgDial</th>
<th>Ch</th>
<th>ArgDial%</th>
<th>Acc</th>
<th>ArgDial%</th>
<th>Rej</th>
<th>ArgDial%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Experiments</td>
<td>121</td>
<td>20</td>
<td>17%</td>
<td>107</td>
<td>88%</td>
<td>14</td>
<td>12%</td>
</tr>
<tr>
<td>Simulation Experiments</td>
<td>121</td>
<td>25</td>
<td>21%</td>
<td>107</td>
<td>88%</td>
<td>14</td>
<td>12%</td>
</tr>
</tbody>
</table>

Table 7.11: Argumentation-based Dialogues triggered during what is found there discussion where Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

master. Thus, robot Fiona sought the human collaborators help and initiated information-seeking dialogue. The human collaborator initiated information-seeking dialogue to seek help from the robot Fiona when he/she (human collaborator) did not know “how many rooms visit” to find treasures but robot Fiona did. In either case, only one of the collaborators (robot Fiona or the human collaborator) had knowledge about “how many rooms to visit.”

- In the physical-robot situation, there were 7 occurrences in which information-seeking dialogues were triggered to discuss “where to search.” The human collaborators challenged robot Fiona in 6 of 7 information-seeking dialogues (86%). All 7 information-seeking dialogues (100%), however, ended in agreements.

- In the simulated-robot situation, there were 11 occurrences in which information-seeking dialogues were triggered to discuss “where to search.” The human collaborators challenged robot Fiona in 6 of 11 (55%) information-seeking dialogues. All 11 information-seeking dialogues (100%), however, ended in agreements.

There were fewer occurrences of information-seeking dialogue during the “how to get there” discussion. In this case, robot Fiona always had the knowledge about “how to get there,” but the human collaborators might or might not had that knowledge.

- In the physical-robot situation, only one of six (17%) information-seeking dialogues was challenged by the human collaborators. All six information-seeking dialogues (100%) during “how to get there” discussions ended in agreement.

- In the simulated-robot situation, only one of two information-seeking dialogues was
challenged by the human collaborators. All six information-seeking dialogues (100%) during “how to get there” discussions ended in agreement.

There were only more occurrences of information-seeking dialogue during the “what is found there” discussion. In this case, robot Fiona did not have the knowledge about “how to identify treasure” but the robot Fiona believed that the human collaborator had that knowledge.

– In the physical-robot situation, only 20 of 121 (17%) information-seeking dialogues were challenged. Almost all (107) information-seeking dialogues (88%) during “what is found there” discussion ended in agreement.

– In the simulated-robot situation, only 25 of 121 (21%) information-seeking dialogues were challenged. Almost all (107) information-seeking dialogues (88%) during “what is found there” discussion ended in agreement.

• Persuasion Dialogue: In this dialogue scenario, the robot believed $b$ and human believed $\neg b$, therefore, they were in disagreement and persuasion dialogue would be triggered. This sets the belief value for $\neg b \in \Gamma_R(H)$.

– In the physical-robot situation, there were 11 occurrences in which persuasion dialogues were triggered to discuss “where to search.” The human collaborator challenged robot Fiona in 7 of 11 persuasion dialogues (64%) during “where to search” discussions. Only two persuasion dialogues (18%), however, ended in disagreement, and the remaining nine persuasion dialogues (85%) ended in agreements.

– In the physical-robot situation, there were 16 occurrences in which persuasion dialogues were triggered to discuss “where to search.” The human collaborators challenged robot Fiona in 10 of 16 persuasion dialogues (63%) during “where to search” discussions. Only two persuasion dialogues (13%), however, ended in disagreement, and the remaining fourteen persuasion dialogues (88%) ended in agreements.
There were more instances where robot Fiona initiated persuasion dialogues with the human collaborator during “how to get there” discussions.

– In the physical-robot situation, the human collaborators challenged robot Fiona in 8 of 12 persuasion dialogues (67%). Only two persuasion dialogues (17%), however, ended in disagreement, and the remaining ten persuasion dialogues (83%) ended in agreements.

– In the physical-robot situation, the human collaborators challenged robot Fiona in 12 of 20 persuasion dialogues (60%). Only five persuasion dialogues (25%), however, ended in disagreement, and the remaining fifteen persuasion dialogues (75%) ended in agreements.

There were no persuasion dialogue during “what is found there” discussion since robot Fiona did not have the knowledge about “how to identify treasure”.

• Inquiry Dialogue:

In this dialogue scenario, neither robot Fiona nor the human collaborator had the full knowledge regarding “how many rooms to visit?” or “what is found there?”. This dialogue scenario sets the value for \( ?b \in \Delta_R \) and the robot’s belief value of human’s belief for \( ?b \in \Gamma_R(H) \). Thus, inquiry dialogues were triggered to explore solutions.

There were fewer occurrences of inquiry dialogues during “where to search discussion”.

– There were only 3 occurrences of inquiry dialogues in both physical and simulation experiments initiated by the robot Fiona with the human collaborator to discuss “where to search.” All 3 inquiry dialogues ended in agreements.

There were no inquiry dialogue during “how to get there” discussion since robot Fiona always had the knowledge about “how to get there”. Therefore, if the human collaborator did not know, an information-seeking dialogue was triggered.
There were more inquiry dialogues occurred during “what is found there discussion”.

- In the physical-robot situation, there were 26 instances of inquiry dialogues between robot Fiona and human collaborators. Human collaborators challenged robot Fiona in 7 of 26 inquiry dialogues (27%) during “what is found there” discussions. Only 8 inquiry dialogues (31%), however, ended in disagreement, and the remaining 18 inquiry dialogues (69%) ended in agreements.

- In the simulated-robot situation, there were 27 instances of inquiry dialogues between robot Fiona and human collaborators. Human collaborators challenged robot Fiona in 12 of 27 inquiry dialogues (44%) during “what is found there” discussions. Only 6 inquiry dialogues (22%), however, ended in disagreement, and the remaining 21 inquiry dialogues (78%) ended in agreements.

Discussion

The three argumentation-based dialogues proposed in this thesis provided the following types of human-robot interaction during collaboration:

- Information-seeking dialogue during “where to search” and “how to get there” discussions implied that the human collaborator sought robot Fiona’s help. Our analysis suggests that humans frequently asked for robot Fiona’s help when there was a lack of information during “where to search” discussions.

- In the physical-robot situation, there were seven information-seeking dialogues that occurred during “where to search” discussions compared to only six information-seeking dialogues that occurred during how to get there discussions.

- In the simulated-robot situation, there were eleven information-seeking dialogues that occurred during “where to search” discussions compared to only two information-seeking dialogues that occurred during how to get there discussions.
Robot Fiona challenges to the human collaborator during inquiry or information-seeking dialogue implied that the robot Fiona attempted to correct the human collaborator. For example, in our experiment, robot Fiona had knowledge of the color of each treasure but did not know the shape of the treasure. By default, robot Fiona believed that the human collaborator had the knowledge to identify both the color and shape of the treasure looking at images taken after visiting a room. Thus, robot Fiona engaged in an information-seeking dialogue. If the human collaborator chose the wrong color for the treasure, robot Fiona would challenge the human collaborator attempting to correct her treasure choice. If the human participant responds to the challenge stating that “no, I am not sure,” the information-seeking dialogue gets terminated. This would set the robots belief as follows: “The human participant does not know the identity of the treasure.” This would trigger an inquiry dialogue where robot Fiona would propose a treasure to the human collaborator based on the color information of the treasure it has. If the human agrees with the proposal, this implies successful human-robot collaboration in which the human collaborator and the robot Fiona together correctly identify the treasure. Our analysis suggests that human collaborators agreed with the robot Fiona even though they frequently challenged the robot. We think that the ability to argue or challenge is crucial for successful collaboration.

Persuasion dialogue led by Robot Fiona indicated that robot Fiona had a better solution than the human collaborator. Thus if the human participants agreed with robot Fiona, it would improve their collaborative goal. For example, if the robot Fiona successfully persuaded the human collaborator to take its proposed efficient path to visit an agreed upon room, the total execution time would be lower. There were 59 persuasion dialogues incidents in all the experiments. Only 11 of 59 persuasion dialogues (19%) ended in disagreement. Forty-eight of 59 persuasion dialogues (81%) ended in an agreement in which robot Fiona successfully persuaded the human collaborator.

Finally, “no dialogue” indicates that both human collaborator and robot Fiona were in agree-
ment about their decision, for example, when robot Fiona and the human collaborator chose the same number of rooms to visit.

**Observations**

An analysis of argumentation-based dialogues during final User Study 2 (Chapter 7) has led to the following observations:

- Humans seek help when they are uncertain about something. Results from the final User Study 2 suggest that a significant number of human participants did not know where to search, were without clues, and as a result, sought help during the where-to-search dialogue. This theory was validated by the results from final User Study 2 who engaged in info-seeking dialogues. (100% 18 out of 42) that occurred during where-to-search ended in agreement even robot was challenged (67% 12 out of 18) the humans and the choice was randomly generated by the game master, they agreed with the robot.

- Humans are reluctant to get help when they are certain about something. For instance, results from the final and User Study 2 detailed in Chapter 7.4 reported that robot peers challenged humans in 45 of 242 argumentation-based dialogues (19%). These challenges occurred during what-is-found-there discussions and were intended to prevent human collaborators from mistakenly detecting a wrong image. Note that these challenges include repeated challenges until the termination of each dialogue. There were 28 out of 45 dialogue occurrences (62%) that ended in disagreement (the 28 disagreements counted for a 12% rejection rate for the 242 argumentation-based dialogues that occurred during the what-is-found-there discussions). The robot in this scenario could only recognize colors and did not know how to detect treasures. It appeared to be less confident about the evidence provided to humans. The results suggest that robots may have failed to prevent human-errors in those cases because the human participants were confident about their selections. It may also be that humans unwarrantedly trust their judgments over anything else.
If humans think they know something but are not absolutely sure, or there is evidence presented that suggests otherwise, they will change their minds. For instance, results from the final and User Study 2 reported that the robot as peer persuaded 85% (23 out of 27) human participants to change course during where-to-search and how-to-get-there discussions. The robot failed to persuade 15% (4 out of 27) of humans to change course although in the 27 challenges 17 (63%) were asked to provide evidence to human participants.
Chapter 8

Conclusion

This chapter summarizes the contributions of my research in Section 8.1, and Section 8.2 details future directions.

8.1 Research Contribution

My research has contributed to both the human-robot interaction (HRI) and argumentation communities by:

- developing a logic-based theoretical dialogue framework and methodology for implementing dialogue protocols to support peer interaction during human-robot collaboration. The research is based on theoretical models found in the literature on argumentation theory and argumentation-based dialogue games, as detailed in Chapter 4.1. It provides a structured method for a robot to maintain its own beliefs, its beliefs about its human partners belief in engaging in an argumentation-based dialogue, and for a robot to make decisions about shared tasks;

- theorizing and formalizing three different argumentation-based collaborative dialogues to support peer interaction: persuasion, information-seeking, and inquiry dialogues, as detailed
in Chapter 4.2. These dialogues seek to resolve disagreements or expand individual or shared knowledge. The research presented in this thesis introduces a formal model of a Treasure Hunt Game in a treasure search domain, a controlled HRI environment for urban search and rescue detailed in Chapter 4.3. In that controlled HRI environment, a human and robot can engage in these three dialogues when required to help each other make informed shared-decisions during peer interaction, as detailed in Chapter 4.4:

– when a human and robot collaborate as peers they can resolve disagreements by engaging in a persuasion dialogue to alter each other’s conflicting beliefs during a shared task and thereby prevent human or robot errors. My research presents how a robot can challenge a human collaborator by engaging in persuasion dialogue during peer interaction, as detailed in Chapter 4. For instance, if a human collaborator’s proposed plan of “how to get there” proves infeasible and may cause task failure in a controlled treasure search domain as detailed in Chapter 4, the robot may disagree with the human collaborator because it does not have sufficient energy to successfully complete the human collaborator’s plan. In this scenario, results from the final and phase 2 user study detailed in Chapter 7 demonstrated that the task completion time and distance traveled were reduced, if the robot successfully persuaded the human collaborator to change its plan to an efficient path.

– a robot or human can expand each other’s individual knowledge by employing an information-seeking dialogue when a human discovers new information that a robot or does not know or vice versa. My research demonstrated how a robot working as a peer can rely on a human collaborator by engaging in an information-seeking dialogue. For example, it may it may require help identifying a treasure. It engages in information-seeking dialogues when it assumes that the human knows how to identify the treasure. An information-seeking dialogue, as presented in this thesis, can be adopted to mimic a rescue robots search for victims in an urban search and rescue domain.
– a robot or human working as peers can expand their shared knowledge by employing an inquiry dialogue to explore the answers to questions to which neither knows the answers and thus *recover from a failure*. The research presented in this thesis demonstrated how a robot and a human can rely on each other by engaging in an inquiry dialogue to identify a treasure. When both human and robot collaborate as peers but do not know how to identify a treasure, an inquiry dialogue can be adopted to mimic a rescue robots search for victims in an urban search and rescue domain.

– a robot or human can challenge its counterpart during persuasion, information-seeking, or inquiry dialogues to prevent possible human or robot related errors. The research presented in this thesis demonstrated how a robot or a human collaborator working as a peer can challenge each other during treasure selection (the “what is found there” discussion), mutual goal selection (e.g., “where to search discussion”), or in devising a plan (e.g., “how to get there discussion”) in the Treasure Hunt Game domain. The argumentation-based dialogue developed in my work can be adopted to a scenario in which a rescue robot challenges a human or vice versa to prevent human or robot errors.

• demonstrating a practical, real-time implementation in which persuasion, inquiry, and information-seeking dialogue are applied to shared decision making for human-robot collaboration in the treasure search domain, as detailed in Chapter 5.

• presenting the results from the subjective analysis of an HRI system that is capable of peer interaction and employing argumentation-based dialogue for shared-decision making during human-robot collaboration in a treasure search domain. The analysis compares the peer interaction system to an HRI system that is solely supervisory. The experiment involved 108 human participants across multiple user studies, as detailed in Chapter 6 and Chapter 7.

• presenting the results from the objective analysis of an HRI system that is capable of peer interaction employing argumentation-based dialogue for shared-decision making during human-robot collaboration in a treasure search domain.
robot collaboration in a treasure search domain. The analysis compares the peer interaction system to an HRI system that is solely supervisory. The experiment involved 108 human participants across multiple user studies detailed in Chapter 7.

This dissertation involves a series of user studies with 108 human participants and investigates two research questions:

1. **Research Question:** Does adding peer interaction-enabled through argumentation-based dialogue to an HRI system improve system performance during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?

   The final user study 2 (physical $n = 27$ and simulation $n = 33$) detailed in Chapter 7 investigated the impact on system performance of adding a full dialogue argumentation-based dialogue to a human-robot interactive system. The final user study compared HRI systems that are capable of peer interaction and employed argumentation-based dialogue and an HRI system that is only capable of supervisory interaction with minimal-dialogue. Results from an objective analysis show that overall system performance improved when a human collaborator engaged in peer interaction with a robot that used argumentation-based dialogue. The human-robot partners made decisions about shared tasks in a search domain and outperformed an HRI system that lacked opportunities for human and robot collaborative decision making. In minimal dialogue the robot acts as a subordinate in supervisory interaction and obeys human commands.

2. **Research Question:** Does adding peer interaction-enabled through argumentation-based dialogue to an HRI system improve user experience during a collaborative task when compared to an HRI system that is capable of only supervisory interaction with minimal dialogue?
The final user study 2 (physical $n = 27$ and simulation $n = 33$) and preliminary user studies, including the pilot study ($n = 9$) and user study 2 (physical $n = 19$ and simulation $n = 20$) detailed in Chapter 6, investigated the impact of user experience with argumentation-based dialogue. Results from the subjective analysis involving 108 human participants across multiple studies show that the human collaborators who engaged in peer interaction with a robot using argumentation-based dialogue perceived the system as similar if not better than an HRI system without argumentation-based dialogue interaction. It performed similar or better than a system engaged in supervisory interaction with minimal-dialogue.

To my knowledge, argumentation theory and argumentation-based dialogue have not been applied to the human-robot interaction domain. The work presented in this thesis is the first to apply argumentation theory and three different logic-based argumentation-dialogues to human-robot collaboration as it seeks to share, challenge and expand knowledge, or persuade partners to resolve conflicts that align with their beliefs.

### 8.2 Future Work

The results from the user studies suggest that even for a simple task a HRI system capable of supporting peer interaction with full dialogue argumentation-based dialogue in a search and rescue domain is beneficial for improving system performance and user experience for collaborating humans and robots. This is despite traditional expectations of supervisory interaction for simple tasks in which human collaborators do not require much help. My research demonstrated that peer interaction-enabled through argumentation-based dialogue can support expansion of individual or shared knowledge. It can aid in the resolution of disagreements and thus prevent human or robot errors, and it may reduce task completion time and increase task success during a collaborative task. In contrast to peer interaction-enabled through argumentation-based dialogue is minimal-dialogue supervisory human-robot interaction in which as a robot acts as a subordinate and listens to and
obeys only human supervisory commands. A logic-based dialogue framework for human-robot collaboration has been developed in which a human and robot can employ argumentation-based dialogue. Three different argumentation-based dialogues have been formalized for human-robot interaction.

The research presented in this thesis does not claim that peer interaction-enabled through argumentation-based dialogue is the only solution for enhancing peer interaction during human-robot collaboration. It rather suggests that argumentation-based dialogue is a good candidate for peer interaction and that it can aid human decision making during human-robot collaboration. My research also does not claim that the argumentation-based dialogue presented here is the pure implementation of an argumentation-based theoretical framework. Rather, it adopts a formal logic-based dialogue framework in the practical domain of human-robot collaboration. Future work will investigate whether there were any discernible attitudinal changes in human perceptions between the pre-surveys that cover the minimal-dialogue and full-dialogue robots.

In my research, I accept that there are many applications in HRI that do not require peer interaction. Instead, supervisory interaction will be sufficient. Peer interaction will require an HRI system to support a system that resembles human-human peer collaboration for humans and robots. Human-robot collaborators will use that system to seek information from each other to minimize uncertainty, expand individual and shared knowledge, and challenge or persuade each other.

The analysis of argumentation-based dialogues during the final user study (Chapter 7.4) suggests several opportunities for a full-dialogue that employs argumentation-based dialogue during peer interaction in the following human-robot collaboration scenarios:

- **Complex Task**: When the robot and the human collaborator do not know how to address all issues in a complex task, both parties can engage in an inquiry dialogue to explore problems surrounding the complex task.

- **Computationally Expensive Decisions**: A robot is better equipped to do computationally expensive tasks faster than the human collaborator. The human collaborator can gather in-
formation from the robot employing an information-seeking dialogue.

- **Lack of Knowledge**: Humans may lack knowledge about a robot’s capabilities or information about a physical environment. Similarly, the robot may lack knowledge that humans may have. The human collaborator can employ an information-seeking dialogue to inquire about information from the robot collaborator and vice-versa.

- **Dynamic Changes**: Humans can seek information using an information-seeking dialogue or use an inquiry dialogue from the robot when dynamic changes (e.g., a sudden obstacle) occur in the environment. One or more dialogues can be embedded inside the inquiry dialogue to explore dynamic changes in the collaborative task.

- **Multiple Unknowns**: A task can be considered complex where there are multiple unknowns. In this case, the human and robot may need to engage in information-seeking and inquiry dialogues.

- **Conflicts**: When the human user and the robot hold opposing beliefs, thereby causing a conflict, there is an opportunity for persuasion dialogue. For example, when a human and a robot have different agendas, as occurred during the full-dialogue mode, the robot will attempt to persuade the human of the efficacy of its agenda by providing an “effective agenda” justification. The human might not be persuaded, however, when the task is critical, and, as a result, the robot has to follow the human’s proposed agenda.

Future work will involve extending this research to hard-to-solve problems as follows:

- There is a need for human-robot dialogue support for more complex task domains in which there are common goals.

- There is a need for human-robot dialogue support for peer interaction between humans and multi-robot teams that have different goals.
• There is a need for bridging the logic-based dialogue research presented in this thesis to natural language research and exploring natural language implementations of argumentation-based dialogue.

Human-robot dialogue that can aid shared decision making, supports the expansion of individual or shared knowledge, and resolves disagreements between collaborative human-robot teams will be much sought after as human society transitions from a world of robot-as-a-tool to robot-as-a partner. My research presents a version of peer interaction enabled through argumentation-based dialogue and allows humans and robots to work together as partners.
Appendices
Appendix A

ArgTrust and HRTeam

A.1 HRTeam Commands and Data Collection

- *Deliberation Time:* Deliberation time is calculated by measuring decision-making time for the human collaborator for a task. This is computed by comparing the time between INIT and MOVE_START commands, which are explained below.

  The INIT command establishes a connection between ArgHRI and HRTeam at the beginning of a task scenario. It is the time when the human collaborator is presented with the collaborative task. The INIT command is logged in the central server as follows:

  ```
  Syntax: TIME [STATUS] <type> <name> <?> <?>
  [FROM] <name> <id0>
  Example: 15:11:24:798:040 [RECEIVED] INIT gui ArgHRI 0
  [FROM] ArgHRI 1394996933
  ```

- MOVE_START command is sent to the robot from ArgHRI to the central server of HRTeam after the deliberation is complete. This command is logged in the central server as follow:
• **Task Completion Time:** Task completion time refers to the amount of time that the robot takes to complete a task. It will be computed between

\[ \text{MOVE\_START} \quad \text{and} \quad \text{AUCTION\_FINISHED} \]

commands which are explained below:

– **MOVE\_START**

command is sent to the robot from ArgHRI to the central server of HRTeam after the deliberation is complete. This

\[ \text{MOVE\_START} \]

is logged in the central server as follow:

\begin{verbatim}
Syntax : TIME [ RECEIVED ] MOVE\_START <robot\_id> [ FROM ] <name> <id0>
\end{verbatim}

• **AUCTION\_FINISHED**

command is logged in the central server of the HRTeam after the robot completes all tasks to which it has been assigned, i.e., after it has visited all the rooms agreed upon by the human and the robot in *full-dialogue mode.*
A.2 XML for ArgTrust

A.2.1 input XML for ArgTrust

<argtrust>
<!-- INPUT XML -->
<domain>
<constant>Room1</constant>
<constant>Room2</constant>
<predicate>At</predicate>
<predicate>GoTo</predicate>
</domain>

<trustnet>
<agent> Me </agent>
<agent> Human </agent>

<!-- my-Robot- trust -->
<trust>
<truster> Human </truster>
<trustee> Me </trustee>
<level> 1 </level>
</trust>

<trust>
<truster> Me </truster>
<trustee> Human </trustee>
</trust>

</trustnet>
</argtrust>
<!-- robot’s beliefs -->

<belief>
<agent> Me </agent>
<rule>
<premise> At(Room1) </premise>
$conclusion> NOT At(Room2) </conclusion>
</rule>
<level> 1 </level>
</belief>

<belief>
<agent> Me </agent>
<rule>
<premise> At(Room2) </premise>
$conclusion> NOT At(Room1) </conclusion>
</rule>
<level> 1 </level>
</belief>

169
<agent> Me </agent>

<rule>
<premise> NOT At(Room2) </premise>
<premise> At(Room1) </premise>
<conclusion> GoTo(Room2) </conclusion>
</rule>

[level> 1 </level>
</belief>

<belief>
<agent> Me </agent>

<rule>
<premise> At(Room2) </premise>
<conclusion> NOT GoTo(Room2) </conclusion>
</rule>

[level> 1 </level>
</belief>

<belief>
<agent> Me </agent>

<rule>
<premise> At(Room1) </premise>
<conclusion> NOT GoTo(Room1) </conclusion>
</rule>

[level> 1 </level>
</belief>
<belief>
  <agent> Me </agent>
  <fact> At(Room1) </fact>
  <level> 1 </level>
</belief>

<belief>
  <agent> Human </agent>
  <fact> At(Room2) </fact>
  <level> 1 </level>
</belief>

</beliefbase>

<query>
  <agent> Me </agent>
  <question> GoTo(Room2) </question>
</query>

</argtrust>

A.2.2 Output XML file from ArgTrust

<argtrust>
<!-- OUTPUT XML -->

171
<agents>
<agent id="agent1">Me</agent>
<agent id="agent2">Human</agent>
</agents>

<beliefs>

<belief id="fact2026" level="1.00" status="UNDEC">At(Room1)</belief>
<belief id="fact2027" level="1.00" status="UNDEC">At(Room2)</belief>

<belief id="rule2896" level="1.00">
<rule>NOT(At(Room2)) :- At(Room1)</rule>
<conclusion id="inference2896" status="UNDEC">NOT(At(Room2))</conclusion>
</belief>

<belief id="rule2897" level="1.00">
<rule>NOT(At(Room1)) :- At(Room2)</rule>
<conclusion id="inference2897" status="UNDEC">NOT(At(Room1))</conclusion>
</belief>

<belief id="rule2898" level="1.00">
<rule>GoTo(Room2) :- NOT(At(Room2)), At(Room1)</rule>
<conclusion id="inference2898" status="UNDEC">GoTo(Room2)</conclusion>
</belief>

</beliefs>
<belief id="rule2899" level="1.00">
<rule>NOT(GoTo(Room2)) :- At(Room2)</rule>
<conclusion id="inference2899" status="UNDEC">
NOT(GoTo(Room2))</conclusion>
</belief>
</beliefs>

<attacks>
<attack>
<from>inference2898</from>
<to>inference2899</to>
?type>rebut</type>
</attack>
<attack>
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<to>inference2898</to>
?type>undermine</type>
</attack>
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<to>inference2896</to>
?type>undermine</type>
</attack>
</attacks>
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<to>inference2897</to>
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<attack>
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<to>fact2027</to>
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<to>inference2899</to>
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</attack>
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<to>inference2898</to>
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<attack>
<from>fact2027</from>

<to>inference2896</to>
<type>rebut</type>
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<attack>
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<to>inference2897</to>
<type>rebut</type>
</attack>

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<to>inference2898</to>
<type>rebut</type>
</attack>

</attacks>
</argtrust>
Appendix B

Final User Study Survey Questionnaire

The sequence of each experiment during User Study 2 ran like this:

- step 1: complete informed consent
- step 2: provide experimental instructions
- step 3: complete pre-survey
- step 4: complete first experiment (minimal dialogue mode or full dialogue mode)
- step 5: complete mid-survey
- step 6: complete second experiment (minimal dialogue mode or full dialogue mode that was not employed in step 4)
- step 7: complete post-survey

Table B.1 has sample sequences of several experimental runs:

Note that we refer Robot Mary with minimal-dialogue mode and Robot Fiona with full-dialogue mode during experiments to make the dialogue mode transparent to the human participants.
Table B.1: User Study 2 Experimental Procedures

**Game Instructions**

All human participants were given verbal and the following written instructions regarding experiments in step 2.

**Welcome to the Treasure Hunt Game**

- **Goal:** There are 1-4 treasures hidden in the map. Your goal is to collaborate with a robot to find those treasures. Good Luck!

- **Rules:**
  
  - There are six rooms.
  
  - Up to 4 treasures could be located in arena. Each treasure is worth 400 points. However, you will lose 150 points for not finding a treasure or misidentifying a treasure.

  - Robot has limited health which is displayed separately than the score for finding treasure. Robot will lose 150 health points for traveling to a room.

  - Robot will lose 50 points for capturing one image. The Robot takes five pictures for each visited room that will cost it total 250 points. Therefore, Robot can only visit a limited number of rooms based on health points.

  - All submission are finals unless otherwise noted. For example, you can not go back to previous window interface after you make your submission. It
is very important that you take your time to make your submission during interaction.

– You will interact with two different robots namely **Robot Mary** and **Robot Fiona**.

– Your goal is to find all the treasures in the shortest amount of time, collaborating with the robot.

* Regarding Experiments:

– You will participate in a series of two experiments.

– Each experiment will employ either interacting with **Robot Mary** or **Robot Fiona**.

– You will be given **pre-survey** before the experiment starts.

– Then after the first experiment you will be given a **mid-survey** that relates to previous experiment.

– Finally, you will be given the post survey after you complete the final experiment.

Please don’t hesitate to ask questions to the experiment moderator if you have any questions.

Thank you

Sincerely,

ArgHRI Team
Surveys.

Human subjects will be asked to complete three surveys:

- *Pre-survey*—given before the first experimental condition.
- *Mid-survey*—given between the first and second experiment.
- *Post-survey*—given after the second experiment.

**Pre-survey**

**Demographic and Background**

1. What is your gender?
   - Female
   - Male

2. What is your age?
   - 18-24
   - 25-39
   - 40-64
   - 65 and over

3. What level in school are you currently?
   - Not a student
   - Pre-college student
   - Freshman (first year undergraduate)
   - Sophomore (second year undergraduate)
• Junior (third year undergraduate)
• Senior (fourth year undergraduate)
• Masters student
• Doctoral student

4. What is your highest level of education?

• No formal education
• K-12 (but not graduated from high school)
• High School Diploma (or GED)
• Some College (but no college degree)
• Professional Certificate (but no college)
• Associates Degree (AS, AA, etc)
• Bachelors Degree (BA, BS, etc)
• Masters Degree (MA, MS, MFA, etc)
• Doctoral Degree (PhD, ScD, MD, etc)
5. How often do you use a computer (i.e., laptop or desktop)? (This could be for anything, like email, games, shopping and/or work.)

- Several times a day
- At least once a day
- Several times a week
- Infrequently
- Never

- less than a year part of job
- more than a year part of my job
Pre-survey

• Please read the following before you start the survey:

Please consider the Treasure Hunt Game (THG) scenario as described earlier while responding to the following survey. In the THG you and a robot work together to find treasures hidden treasures an arena.

• Pre-Survey: Section 1

1. I think that I can collaborate successfully with a robot in this treasure hunt game.

   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree disagree

2. I think that a robot can be a trustworthy collaborator.

   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree disagree

3. I don’t think that I have to expend a lot of effort to communicate with a robot.

   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree disagree

4. I think that I can be successful at the Treasure Hunt Game without a robot’s help.

   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree disagree
5. In general, I find it easier to work alone.

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
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<td>somewhat disagree</td>
<td>disagree</td>
<td>neither</td>
<td>somewhat agree</td>
<td>agree</td>
<td>strongly agree</td>
</tr>
<tr>
<td>disagree</td>
<td>agree</td>
<td>strongly agree</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
• Pre-Survey: Section II

1. I think that collaborating with a robot will make my task easier than working on the task alone.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

2. I think that the robot will provide me with reliable information that will help me succeed in the task.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

3. I think that I can complete the task quickly while getting help from the robot.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

4. I trust the robot to catch something I miss while I am making my decision.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

5. I think that discussing with the robot will slow me down to make the decision.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree
Survey: Robot Mary

• Please read the following before you start the survey:

Please consider the Treasure Hunt Game (THG) scenario you just experienced in the previous experiment while responding to the following survey.

• Survey 2: Section I

1. I thought that I collaborated successfully with Robot Mary in this treasure hunt game.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

2. I thought that Robot Mary was a trustworthy collaborator.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

3. I didn’t think that I had to expend a lot of effort to communicate with Robot Mary.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

4. I thought that I was successful at the Treasure Hunt Game without Robot Mary’s help.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

5. In general, I find it easier to work alone.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree
1. I thought that collaborating with Robot Mary made my task easier than working on the task alone.
   (1) strongly disagree (2) somewhat disagree (3) disagree (4) neither (5) somewhat agree (6) agree (7) strongly agree

2. I thought that Robot Mary provided me with reliable information that helped me succeed in the task.
   (1) strongly disagree (2) somewhat disagree (3) disagree (4) neither (5) somewhat agree (6) agree (7) strongly agree

3. I thought that I completed the task quickly because I got help from Robot Mary.
   (1) strongly disagree (2) somewhat disagree (3) disagree (4) neither (5) somewhat agree (6) agree (7) strongly agree

4. I thought that Robot Mary slowed me down to make decisions.
   (1) strongly disagree (2) somewhat disagree (3) disagree (4) neither (5) somewhat agree (6) agree (7) strongly agree

5. I trusted Robot Mary to catch something I missed while I was making decisions.
   (1) strongly disagree (2) somewhat disagree (3) disagree (4) neither (5) somewhat agree (6) agree (7) strongly agree
Survey for Robot Fiona

- Please consider the Treasure Hunt Game (THG) scenario you just experienced while responding to the following survey.

- Survey for Robot Fiona: Section I

1. I thought that I collaborated successfully with Robot Fiona in this treasure hunt game.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

2. I didn’t think that I had to expend a lot of effort to communicate with Robot Fiona.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

3. I thought that Robot Fiona was a trustworthy collaborator.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

4. I thought that I was successful at the Treasure Hunt Game without Robot’s Fiona’s help.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree

5. In general, I find it easier to work alone.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly
   disagree agree
1. I thought that collaborating with Robot Fiona made my task easier than working on the task alone.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

2. I thought that Robot Fiona provided me reliable information that helped me succeed in the task.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

3. I thought that I completed the task quickly because I got help from Robot Fiona.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

4. I trusted Robot Fiona to catch something I missed while I was making decisions.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree

5. I thought that Robot Fiona slowed me down to make decisions.
   (1) (2) (3) (4) (5) (6) (7)
   strongly somewhat disagree disagree neither somewhat agree agree strongly disagree agree
• Post-Survey: Section III

– Please consider the Treasure Hunt Game (THG) scenario you just experienced while responding to the following survey:

– Robot Mary does not provide feedback.

– Robot Fiona provides feedback.

1. How difficult was each scenario to understand?

   (1)  (2)  (3)  (4)  (5)  (6)  (7)
   very somewhat easy easy neither somewhat difficult difficult strongly
easy                       difficult

2. Given a simple task,

   a. I prefer Robot Mary that does not provide any feedback
   b. I prefer Robot Fiona that provides feedback.

3. Given a complex task,

   a. I prefer Robot Mary that does not provide any feedback.
   b. I prefer Robot Fiona that provides feedback.

4. How well would you say you understood the task while interacting with Robot Mary that did not provide any feedback?

   very poor  (1)  (2)  (3)  (4)  (5)  (6)  (7)  very well

5. How well would you say you understood the task while interacting with Robot Fiona that provided feedback?

   very poor  (1)  (2)  (3)  (4)  (5)  (6)  (7)  very well

6. How much did the Robot Fiona’s feedback help you resolve problems?

   not helpful at all  (1)  (2)  (3)  (4)  (5)  (6)  (7)  very helpful
7. How mentally demanding was the task while interacting with Robot *Mary* that did not provide any feedback?
   not demanding at all (1) (2) (3) (4) (5) (6) (7) very demanding

8. How mentally demanding was the task while interacting with Robot *Fiona* that provided feedback?
   not demanding at all (1) (2) (3) (4) (5) (6) (7) very demanding

9. How hard was it to make a decision (or come up with a plan to solve the game)?
   very easy (1) (2) (3) (4) (5) (6) (7) very difficult

10. How much did the Robot *Fiona’s* feedback help your decision making?
    not helpful at all (1) (2) (3) (4) (5) (6) (7) very helpful

11. Please explain how and if the Robot *Fiona’s* feedback during helped with your decision making.
Appendix C

A Live ArgHRI System Demonstration

This section demonstrates how the ArgHRI System (ArgHRI 2.0) was used by recreating detailed human-robot interaction examples that analyze two individual Treasure Hunt Games. A human participant played both games in the final user study in the THG domain. To maintain anonymity, the human participant is referred to as User12 for the remainder of this section. The robot is referred to as Robot Mary while operating in supervisory interaction with minimal-dialogue mode and Robot Fiona while operating in peer interaction with full-dialogue mode, to make the experimental dialogue mode transparent to the human participants (detailed in Chapter 7). User12 played the second game (Game2) collaborating with Robot Mary and the first game (Game1) collaborating with Robot Fiona.

The human-robot interaction example for User12 was recreated analyzing various logs recorded by the ArgHRI Log Manager during both games as described below:

- Experimental setups were recreated analyzing logged data from the welcome panel in the ArgHRI 2.0 User Interface.

- Graphical user interface events were recreated analyzing a GUI event log from the ArgHRI Interface Manager module during the THG.

- The Treasure Hunt Game status was recreated from the game event log generated by the
ArgHRI Game Manager module.

- Dialogues between robot and human participants were reenacted by analyzing the dialogue event log and GUI event log generated by the ArgHRI Dialogue Manager module and the Interface Manager, respectively.

- The HRTeam log generated by the external HRTeam System module was utilized to simulate the path travelled taken by the robot during the THG.

C.1 Experimental Setup Demonstration

User12, the human collaborator, was brought into the experiment room and given a laptop with the ArgHRI System software at the beginning of the physical experiment. All physical experiments were conducted using a physical robot in our agents lab at Brooklyn College. The ArgHRI System
2.0 was deployed to remotely communicate with the robot since User12 was situated in a different room and could not see the physical arena during experimental runs. User12’s only knowledge of the arena was provided by the robots. The ArgHRI system started with the welcome panel where the Treasure Hunt Game rules were explained. The welcome panel was identical for both Game2 with Robot Mary in \textit{minimal-dialogue} and Game1 with Robot Fiona in \textit{full-dialogue} mode. The game rules in the welcome panel informed User12 that the robots would explore a physical arena that is divided into seven regions: six rooms and a hallway, as shown in Figure C.1[from earlier section]; there were 1-4 treasures hidden in the arena, and the goal of their mission was to find the maximum number of treasures in the shortest amount of time. Neither Robot Mary nor Robot Fiona had enough energy to perform an exhaustive search, so the robot and User12 had to work together to solve their common goal. User12 was asked to decide with Robots Mary and Fiona about “where to search” (i.e., which rooms to search), “how to get there” (i.e., which room-search order to use) and “what is found there” (i.e., identifying treasure analyzing images collected by the robot) during each game. These three dialogue opportunities provide collaborative decision-making opportunities between the human collaborator and robot. The experimental setups for both games played by User12 are summarized in Table C.1, which analyzes GUI logs, as shown in Figure C.3 and C.2.

<table>
<thead>
<tr>
<th>Treasure Hunt Game No</th>
<th>Experimental Dialogue Mode</th>
<th>Robot Type</th>
<th>Treasure Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game1</td>
<td>Robot Fiona (\textit{full-dialogue mode})</td>
<td>Live Robot (Blackfin)</td>
<td>Challenge 1 (Treasure Set 1)</td>
</tr>
<tr>
<td>Game2</td>
<td>Robot Mary (\textit{minimal-dialogue mode})</td>
<td>Live Robot (Blackfin)</td>
<td>Challenge 2 (Treasure Set 2)</td>
</tr>
</tbody>
</table>

Table C.1: Experimental Setups for User12 from Final User Study

The welcome panels for User12 in \textit{minimal-dialogue} (i.e., game 2) and \textit{full-dialogue} mode (i.e., game 1) are recreated in Figure C.11. Figure (B) C.11 is the welcome panel at the beginning of Game2 with Robot Mary and User12 in \textit{minimal-dialogue} mode, as detailed in Section C.2. Figure (A) C.11 is the welcome panel at the beginning of Game1 with Robot Fiona and User12 in \textit{full-dialogue} mode, as detailed in Section C.3.
Figure C.2: Extracted GUI log for experimental setup from Game1 played by User12 and Robot Fiona in *full-dialogue* mode

Figure C.3: Extracted GUI log for experimental setup from Game2 played by User12 and Robot Mary in *minimal-dialogue* mode

### C.2 Minimal-Dialogue Mode Demonstration

User12 interacted with Robot Mary as a supervisor in *minimal-dialogue* mode during Game2. The *minimal-dialogue* panel appears to User12 after the welcome panel (see Figure (B) C.11). With its appearance User12 chose the rooms and order in which Robot Mary was to travel. In *minimal-dialogue* panel, “where to search” and “how to get there” discussions were combined in one dialogue panel since Robot Mary, the robot in minimal-dialogue mode, only obeyed commands given by User12 acting in a supervisory role.

**Deciding “where to search” and “how to get there”**

User12 commanded the robot to search in Room2 first, Room3 second, Room6 third, and Room5 last, in the *minimal dialogue* panel, as recreated in Figure C.5 after analyzing GUI logs shown in Figure C.7 and analyzing Dialogue logs shown in Figure C.6.
Deciding “what is found” there

Robot Mary first traveled to Room2, and it shared the five captured images from that room which were displayed in the image panel along with the treasure identification dialogues, as recreated in Figure C.8. Robot Mary asked whether User12 saw any of the four treasures in the five images displayed in the image panel. User12 erroneously identified the “yellow can” in Room2 and lost 150 points, as shown in Figure C.9. Room2 did not have any hidden treasures. The Game Master delivered game-related messages, including game scores and treasures found, as pop-ups.

<table>
<thead>
<tr>
<th>Room Visited</th>
<th>Treasure In Room</th>
<th>User12’s Selected Treasure</th>
<th>Is User12 Identified Correctly?</th>
<th>Game Master GUI Message</th>
<th>Game Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Room2</td>
<td>None</td>
<td>Yellow Can</td>
<td>No</td>
<td></td>
<td>-150</td>
</tr>
<tr>
<td>Room3</td>
<td>Orange Bottle</td>
<td>Orange Bottle</td>
<td>Yes</td>
<td></td>
<td>(-150+400=) 250</td>
</tr>
<tr>
<td>Room6</td>
<td>Pink Can</td>
<td>Pink Can</td>
<td>Yes</td>
<td></td>
<td>(250+400=) 650</td>
</tr>
<tr>
<td>Room5</td>
<td>None</td>
<td>None</td>
<td>Yes</td>
<td></td>
<td>(650-150=) 500</td>
</tr>
</tbody>
</table>

Table C.2: A Reenacted sample Game Master Messages from Game 2 played by the human subject User12 and Robot Mary in *minimal-dialogue* mode
Figure C.5: The Reenacted ArgHRI Planning Window from the THG Game 2 played by the human subject User12 and Robot Mary in minimal-dialogue mode

```
1 2014−11−21 20:16:40:111 <b>Robot Mary</b> : Welcome to the Treasure Hunt Game! I am Robot Mary. Please let me know which rooms I should visit and in what order.
3 2014−11−21 20:17:23:133 <b>Robot Mary</b> : OK. I am executing your plan to go to Rooms: 2→3→6→5
```

Figure C.6: Extracted Dialogue Logs for Planning from minimal-dialogue panel from THG Game2 played by the human subject User12 and Robot Mary in minimal-dialogue mode
2014−11−21 20:16:57:982 ARGGUI ROOM2 is CHECKED
2014−11−21 20:17:08:045 ARGGUI ROOM3 is CHECKED
2014−11−21 20:17:12:837 ARGGUI ROOM6 is CHECKED
2014−11−21 20:17:20:716 ARGGUI ROOM5 is CHECKED

2014−11−21 20:17:23:135 Robot Mary starts traveling following
User_2014_11_21_T2_P_ND_816 to Rooms: 2-->3-->6-->5
Initial Game Data

Treasure Found: 0 of 3 treasures

Figure C.7: Extracted GUI log from the minimal-dialogue panel of THG Game2, played by User12 and Robot Mary in minimal-dialogue mode

Figure C.8: The Reenacted ArgHRI Treasure Identification Window from THG Game2 played by User12 and Robot Mary in minimal-dialogue mode
Figure C.9: Extracted GUI log from treasure-identification panel from THG Game2 played by User12 and Robot Mary in minimal-dialogue mode
User12’s identified treasures, Game Master messages, and correct treasures for each explored room from Game2 were analyzed using GUI logs, game logs, and dialogue logs. They are summarized in Table C.2. In Game2, Robot Mary employed only minimal scripted dialogues. They were queries to the human and acknowledgements that were in response to the human’s response with “Thank you for the information.”

Figure C.10 shows through an analysis of the HRTeam logs the trajectory path traveled by Robot Mary in Game2.

![Figure C.10: Trajectory Path for Robot Mary (2− > 3− > 6− > 5) from Game 2 played by User12 in minimal-dialogue mode](image)

C.3 Full-Dialogue Mode Demonstration

User12 interacted with Robot Fiona as a peer in full-dialogue mode during Game1. Robot Fiona communicated with the User12 employing structured argumentation-based dialogues in which User12 and the robot interacted with each other as peers and reached agreement about the robot’s actions in the physical THG arena before any actions were taken. The welcome panel in Figure (A) C.11 transitioned to the “where to search” dialogue panel when User12 and Robot Fiona discussed where to look for treasures.
Deciding where to search

Robot Fiona randomly received a clue to search four rooms from the Game Master of the Game Manager module at the start of Game1 according to the experimental design of the final user study. As discussed in earlier in Section 5.2.1, Robot Fiona receives the random clue about the number of rooms to visit from the Game Master. The “I don’t know” option to express the human’s lack of knowledge during the “where to search” discussion was designed to provide opportunities for all three types of argumentation-based dialogues discussed in this thesis. For example, if User12 selected “I don’t know” to express its lack of knowledge, an information-seeking dialogue would have initiated by User12 since the robot had a belief regarding the number of rooms to visit after receiving a clue from the Game Master during Game1. User12, however, selected five rooms in the “where to search” dialogue panel that Robot Fiona should search, according to the extracted GUI log shown in Figure C.12.

Here is the recreated dialogue sequence from the “where to search” discussion that occurred between Robot Fiona and User12 during Game1:

After User12’s selection of the number of rooms to visit in the ArgHRI, Robot Fiona’s belief and its belief about User12’s beliefs were updated. The pre-conditions are described below:
Figure C.12: Extracted GUI Logs for the “where to search” discussion from the full-dialogue panel.

<table>
<thead>
<tr>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b \in \Delta_R$</td>
<td>where $b$ represents the belief that the robot should search exactly four rooms since it received the clue from the Game Master</td>
</tr>
<tr>
<td>$\neg b \in \Gamma(H)$</td>
<td>the robot believed that the human subject User12 believed that the robot should search five rooms</td>
</tr>
</tbody>
</table>

Thus Robot Fiona and User12 have a disagreement:

$$\langle b \in \Delta_R \rangle \text{ and } \langle \neg b \in \Gamma(H) \rangle \rightarrow \text{disagreement (case 4)}$$

Case 4 called for a persuasion dialogue since the conflict between Robot Fiona’s belief and its belief about User12’s beliefs satisfied the pre-conditions for the persuasion dialogue. The Dialogue Manager started a persuasion dialogue initiated by Robot Fiona with User12 as follows:

<table>
<thead>
<tr>
<th>dialogue move</th>
<th>scripted text in chat-style interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>control layer</td>
<td>There is a conflict about the Number of Rooms To Visit.</td>
</tr>
<tr>
<td>assert($R, H, b$)</td>
<td>Robot Fiona: Our goals are different. I believe that we should visit 4 rooms instead of visiting 5 rooms. Do you &quot;Agree&quot; or &quot;Disagree&quot;?</td>
</tr>
</tbody>
</table>

The ArgHRI dialogue panel provided the human collaborator with the following choices from the possible dialogue moves of the persuasion dialogue:
Here, according to the persuasion dialogue protocol, User12 could either accept the robot’s belief by selecting “Agree,” or reject the robot’s belief by selecting “Disagree,” or challenge the robot’s belief by selecting “I would like to know why.” User12 selected “Agree,” then the persuasion dialogue continued as follows:

<table>
<thead>
<tr>
<th>dialogue move</th>
<th>scripted text in chat-style interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>accept((H, R, b))</td>
<td>User12: Yes, I agree with your proposed goal to visit 4 rooms.</td>
</tr>
</tbody>
</table>

Thus Robot Fiona, by employing persuasion dialogue, successfully persuaded User12 of its own belief about searching four rooms instead of the five the human intended.

After successful termination of the persuasion dialogue, Robot Fiona’s beliefs about the human’s beliefs were updated to its belief as described in the post-conditions below.

<table>
<thead>
<tr>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(b \in \Delta_R)</td>
<td>the robot believed that it should search four rooms since it received a clue from the Game Master</td>
</tr>
<tr>
<td>(b \in \Gamma(H))</td>
<td>the robot believed that the human User12 believed that the robot should search four rooms</td>
</tr>
</tbody>
</table>

The ArgHRI Interface scenes for a persuasion dialogue during “where to search” discussions are being recreated in Figure C.15.

User12 then chose to visit Room3, Room4, Room5, and Room6. After User12 and the Robot Fiona finished discussing and decided on “where to search”, the ArgHRI system transitioned to the “how to get there” dialogue panel.
Deciding how to get there

Next User12 and Robot Fiona received a “how to get there” dialogue panel to decide together the order in which Robot Fiona should travel to Room3, Room4, Room5, and Room6. Here User12 could choose “I don’t know” to indicate lack of knowledge. This would trigger an information-seeking dialogue from the human collaborator since Robot Fiona can plan its path, computing the cost of traveling from its starting location (i.e., Room4) to each of the chosen rooms and determine a shortest-path order for visiting the rooms in our Treasure Hunt experimental domain. No dialogue would have occurred had both the robot and human plans been identical.

User12, however, suggested that the robot should visit Room3 first, Room4 second, Room6 third, and Room5 last (See Figure C.14), but during Game2 Robot Fiona computed the shortest-path and chose to visit Room4 first, Room5 second, Room6 third, and Room3 last.

Thus the pre-conditions for the “where to search” discussion during Game2 were as follows:
Figure C.14: A Reenacted ArgHRI Interface Scenes for User12’s initial plans.

<table>
<thead>
<tr>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b \in \Delta_R$</td>
<td>where $b$ represents the belief that Robot Fiona should search Room4 first, Room5 second, Room6 third, and Room3 last</td>
</tr>
<tr>
<td>$b \in \Gamma(H)_R$</td>
<td>Robot Fiona believed that User12 believed that Robot Fiona should search Room3 first, Room4 second, Room6 third, and Room5 last</td>
</tr>
</tbody>
</table>

Thus once again, Robot Fiona and User12 had a disagreement over the “where to search” discussion:

$$\langle b \in \Delta_R \rangle \text{ and } \langle \neg b \in \Gamma(H) \rangle \rightarrow \text{disagreement (case 4)}$$

Case 4 called for a persuasion dialogue because the conflict between Robot Fiona’s belief and its belief about User12’s beliefs satisfied the pre-conditions for the persuasion dialogue. The Dialogue Manager’s control layer started the persuasion dialogue initiated by Robot Fiona with User12 as follows:
There is a conflict about Search Order

Robot Fiona: There is a conflict in our plans, we need to reach an agreement.
I would like to go to Rooms: 4→5→6→3→.
To get the reason for why I disagree with your plan, click "Why"
If you want to continue with my plan, click "Agree"
If you would like to continue with your plan, click "Disagree"

The ArgHRI User Interface provided the human collaborator with the following three choices from the possible dialogue moves for the persuasion dialogue:

<table>
<thead>
<tr>
<th>dialogue move</th>
<th>scripted text in chat-style interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>control layer</td>
<td>Do you agree with the robot?</td>
</tr>
<tr>
<td></td>
<td>◦ Agree</td>
</tr>
<tr>
<td></td>
<td>◦ Disagree</td>
</tr>
<tr>
<td></td>
<td>◦ I would like to know why?</td>
</tr>
</tbody>
</table>

Here according to the persuasion dialogue protocol, User12’s choice would affect Robot Fiona’s actions. If User12 accepted Robot Fiona’s belief by selecting “Agree,” Robot Fiona would execute its own plan. If User12 rejected Robot Fiona’s belief by selecting “Disagree,” Robot Fiona would execute User12’s suggested plan.

During Game2, User12 challenged Robot Fiona’s belief by first selecting “I would like to know why?,” and the persuasion dialogue continued as follows:

<table>
<thead>
<tr>
<th>dialogue move</th>
<th>scripted text in chat-style interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>challenge(R, H, b)</td>
<td>User12: I would like to know why you would like to visit Rooms: 4→5→6→3→</td>
</tr>
<tr>
<td>assert(R, H, S(b))</td>
<td>Robot Fiona: According to my calculation, going to to Rooms: 4→5→6→3→ has a lower cost than your plan of going to Rooms: 3→4→6→5→. Please &quot;Agree&quot; or &quot;Disagree&quot; with my plan.</td>
</tr>
</tbody>
</table>
Here Robot Fiona provided supporting evidence for its belief and response to User12’s challenge. User12 accepted Robot Fiona’s supporting evidence selecting “Agree,” and the persuasion dialogue continued as follows:

<table>
<thead>
<tr>
<th>dialogue move</th>
<th>scripted text in chat-style interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>accept($H, R, b$)</td>
<td>User12: I agree with your plan of going to Rooms: 4− &gt; 5− &gt; 6− &gt; 3− &gt;.</td>
</tr>
</tbody>
</table>

Robot Fiona once again successfully persuaded User12 during Game1, and the persuasion dialogue terminated in agreement. The post-conditions for Robot Fiona’s belief and its belief about the User12’s belief about the plan were updated as follows:

<table>
<thead>
<tr>
<th>beliefs</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b \in \Delta_R$</td>
<td>Robot Fiona believed that it should search Room4 first, Room5 second, Room6 third, and Room3 last</td>
</tr>
<tr>
<td>$b \in \Gamma(H)_R$</td>
<td>Robot Fiona believed that that User12 believed that Robot Fiona should search Room4 first, Room5 second, Room6 third, and Room3 last</td>
</tr>
</tbody>
</table>

Interface scenes for a persuasion dialogue between User12 and Robot Fiona during “how to get there” discussions are recreated in Figure C.15.

**Deciding what is found there**

Next Robot Fiona engaged in four different argumentation-based dialogues as full dialogues to discuss the existence of treasures in each of the four rooms. After Robot Fiona arrived at a chosen room and performed a simulated sensor-sweep task, the five images were displayed in the image panel (See Figure C.16) along with the “what is found there” dialogue panel. Robot Fiona continued traveling to the next room while the human collaborator inspected the five images for possible treasures. As discussed earlier, the image panel only displays the images from the most recently visited room. For example, User12 and Robot Fiona had to decide on “what is found in Room4”
Figure C.15: Reenacted ArgHRI Interface Scenes for a persuasion dialogue during “how to get there” discussions.

before Robot Fiona reached Room5. The image panel displayed the five images from Room4 until the arrival of new images from Room5. Short duration images from each room added implicit time constraints to the THG game play to make the game play engaging and challenging. Robot Fiona, however, depended on User12 to identify treasure because it did not know how to identify treasure.

Robot Fiona had a lack of knowledge about the existence of treasure in Room4 (i.e., $\exists b \in \Delta_R$) and believed that User12 knew if there was treasure or not in Room4 (i.e., $b \in \Gamma(H)_R \lor \neg b \in \Gamma(H)_R$). This satisfied the pre-conditions for the information-seeking dialogue (i.e., case 3). Robot Fiona initiated an information-seeking dialogue to discuss “what is found in Room4” with User12:
pre-conditions $\langle ?b \in \Delta_R \rangle$ and $\langle b \in \Gamma(H)_R \lor \neg b \in \Gamma(H)_R \rangle \rightarrow$ lack of knowledge (case 3)

dialogue move scripted text in chat-style interface

question($R, H, b$) Robot Fiona: Do you see any of the following Treasures in Room 4?

User12: I believe that there is a pink can in Room 4.

accept($R, H, b$) Robot Fiona: Great. You are Correct! Game Master also confirmed that pink treasure is in Room 4. We gained 400 points.

User12 correctly identified a treasure in Room 4 and the information-seeking dialogue terminated successfully. Robot Fiona’s belief and its belief about the User12’s belief was updated accordingly.

post-conditions $\langle b \in \Delta_R \rangle$ and $\langle b \in \Gamma(H)_R \rangle$

Robot Fiona initiated three more information-seeking dialogues for each of the remaining three

Figure C.16: Reenacted ArgHRI Interface Treasure Identification Window during “what is found in Room 4” discussion.
rooms. All three information-seeking dialogues terminated successfully since User12 knew which was the correct treasure for each room. Robot Fiona initiated an information-seeking dialogue after reaching Room5 to discuss “what is found in Room5” with User12 and identified no treasure:

### pre-conditions

$$\langle ?b \in \Delta_R \rangle$$ and $$\langle b \in \Gamma(H)_R \lor \neg b \in \Gamma(H)_R \rangle \rightarrow lack\ of\ knowledge\ (case\ 3)$$

<table>
<thead>
<tr>
<th>dialogue move</th>
<th>scripted text in chat-style interface</th>
</tr>
</thead>
<tbody>
<tr>
<td>question($R, H, b$)</td>
<td>Robot Fiona: Do you see any of the following Treasures in Room 5?</td>
</tr>
<tr>
<td>assert($H, R, b$)</td>
<td>User12: I believe that there is no treasure in Room 5</td>
</tr>
<tr>
<td>accept($R, H, b$)</td>
<td>Robot Fiona: You are correct. Game Master also confirmed that there is NO treasure in Room 5. We lost 150 points for not finding any treasure.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>control layer</th>
<th>information-seeking dialogue terminates</th>
</tr>
</thead>
</table>

### post-conditions

$$\langle \neg b \in \Delta_R \rangle$$ and $$\langle \neg b \in \Gamma(H)_R \rangle$$

Robot Fiona initiated an information-seeking dialogue after reaching Room6 to discuss “what is found in Room6” with User12 and identified no treasure:
pre-conditions \[ \langle ?b \in \Delta_R \rangle \text{ and } \langle b \in \Gamma(H)_R \lor \neg b \in \Gamma(H)_R \rangle \rightarrow \text{lack of knowledge (case 3)} \]

dialogue move scripted text in chat-style interface

question \((R, H, b)\)

Robot Fiona: Do you see any of the following Treasures in Room 6?

![Image of a chat interface with options for selecting treasures]

assert \((H, R, b)\)

User12: I believe that there is no treasure in Room 6

accept \((R, H, b)\)

Robot Fiona: You are correct. Game Master also confirmed that there is NO treasure in Room 6.

We lost 150 points for not finding any treasure.

control layer information-seeking dialogue terminates

post-conditions \[ \langle \neg b \in \Delta_R \rangle \text{ and } \langle \neg b \in \Gamma(H)_R \rangle \]

Finally, Robot Fiona initiated an information-seeking dialogue after reaching Room3 to discuss “what is found in Room3” with User12:
pre-conditions \[ \langle b \in \Delta R \rangle \text{ and } \langle b \in \Gamma(H)_R \lor \neg b \in \Gamma(H)_R \rangle \rightarrow \text{lack of knowledge} \text{ (case 3)} \]

dialogue move scripted text in chat-style interface

question \((R, H, b)\) Robot Fiona: Do you see any of the following Treasures in Room 3?

assert \((H, R, b)\) User12: I believe that there is a pink can in Room 3.

accept \((R, H, b)\) Robot Fiona: Great. You are Correct! Game Master also confirmed that yellow can is in Room 3.

We gained 400 points.

control layer information-seeking dialogue terminates

post-conditions \[ \langle b \in \Delta R \rangle \text{ and } \langle b \in \Gamma(H)_R \rangle \]

User12 correctly identified the existence of each of the two hidden treasures from the rooms the robot searched during Game1. The final results of Game1 were analyzed using GUI logs, game logs, and dialogue logs and is summarized in Table C.3.

<table>
<thead>
<tr>
<th>Room Visited</th>
<th>Treasure In Room</th>
<th>User12’s Selected Treasure</th>
<th>Is User12 Identified Correctly?</th>
<th>Game Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Room4</td>
<td>Pink Can</td>
<td>Pink Can</td>
<td>Yes</td>
<td>400</td>
</tr>
<tr>
<td>Room5</td>
<td>None</td>
<td>None</td>
<td>Yes</td>
<td>(400-150=) 250</td>
</tr>
<tr>
<td>Room6</td>
<td>None</td>
<td>None</td>
<td>Yes</td>
<td>(250-150=) 100</td>
</tr>
<tr>
<td>Room3</td>
<td>Yellow Can</td>
<td>Yellow Can</td>
<td>Yes</td>
<td>(100+400=) 500</td>
</tr>
</tbody>
</table>

Table C.3: Results from Game1 played by the human subject User12 and Robot Fiona in full-dialogue mode

Figure C.17 shows the trajectory path traveled by Robot Fiona in Game1 by analyzing the HRTeam logs.

The two games played by User12 were selected out of 120 games played by 60 different human-
Figure C.17: Trajectory Path for Robot Fiona (4→5→6→3) from Game1 played by User12 in full-dialogue mode

subjects from the final user study to demonstrate comprehensive human-robot interaction examples that highlighted different aspects of the ArgHRI 2.0 system. Specifically, the use of argumentation-based dialogues in the ArgHRI 2.0 system was demonstrated above by analyzing how Game1 was played by User 12 with Robot Fiona in full-dialogue mode.
Appendix D

Final User Study Results

This section includes analysis of raw subjective, objective, and dialogue data from the final User Study 2. The following table summarizes all the different categories in Table D.1, which are used in the remainder of the document. Note that we refer Robot Mary with minimal-dialogue mode and Robot Fiona with full-dialogue mode during experiments to make the dialogue mode transparent to the human participants.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>Includes data only from participants in physical experiments</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>Includes participant data only from simulation experiments</td>
</tr>
</tbody>
</table>

Table D.1: ArgDialogue Categories Explained
D.1 Section: Demographic

D.1.1 Gender

• *What is your Gender?*

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>30</td>
<td>22</td>
<td>8</td>
</tr>
<tr>
<td>SIM</td>
<td>33</td>
<td>22</td>
<td>11</td>
</tr>
</tbody>
</table>

D.1.2 Age

• *What is your age?*

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>18-24</th>
<th>25-39</th>
<th>40-64</th>
<th>65 and over</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>30</td>
<td>22</td>
<td>8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SIM</td>
<td>33</td>
<td>21</td>
<td>12</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
D.1.3 Level in School

- *What Level in School are you currently?*

<table>
<thead>
<tr>
<th></th>
<th>Physical</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not a student</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Pre-college student</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Freshman (1st year undergrad.)</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>Sophomore (2nd year undergrad.)</td>
<td>10</td>
<td>21</td>
</tr>
<tr>
<td>Junior (3rd year undergrad.)</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>Senior (4th year undergrad.)</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Masters student</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Doctoral student</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Num. of Part.</td>
<td>30</td>
<td>33</td>
</tr>
</tbody>
</table>

D.1.4 Level of Education

- *What is your highest level of education?*
### D.1.5 Computer Usage

- *How often do you use a computer (i.e., laptop or desktop)? (This could be for anything, like email, games, shopping and/or work.)*

<table>
<thead>
<tr>
<th></th>
<th>Physical</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Several times a day</td>
<td>26</td>
<td>28</td>
</tr>
<tr>
<td>At least once a day</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Several times a week</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Infrequently</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Never</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total participants</td>
<td>30</td>
<td>33</td>
</tr>
</tbody>
</table>
D.1.6 Major

- Write down the subject(s) you are majoring in (you did major in) in college? (Include both subjects for double majors)
<table>
<thead>
<tr>
<th>Course Description</th>
<th>Physical</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computer Science</td>
<td>11</td>
<td>15</td>
</tr>
<tr>
<td>Computer Network Technology</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Computer Information Systems</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>ECE</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Intercultural Communication/German Computer Science</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Liberal Arts</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Computer Science, Applied Mathematics</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Accounting</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Accounting Economic Finance</td>
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<tr>
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<tr>
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<tr>
<td>Liberal Arts, Multimedia Computing</td>
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<tr>
<td>Speech Therapy</td>
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<tr>
<td>Economics and Computer Science</td>
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<tr>
<td>Public accounting and Business management and Finance</td>
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</tr>
<tr>
<td>Computer Science/Multimedia Computing</td>
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<td>Pre Med</td>
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</tr>
<tr>
<td>Music Performance/Music Education</td>
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</tr>
<tr>
<td>Not applicable</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>num of participants</td>
<td>30</td>
<td>33</td>
</tr>
</tbody>
</table>
D.1.7  Robot Experience

- Have you interacted with a robot(s) (e.g., Lego Mindstorm Robot, NXT, Arduino etc.) before today?

<table>
<thead>
<tr>
<th></th>
<th>yes</th>
<th>no</th>
<th>num of participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>16</td>
<td>14</td>
<td>30</td>
</tr>
<tr>
<td>SIM</td>
<td>10</td>
<td>23</td>
<td>33</td>
</tr>
</tbody>
</table>

D.1.8  Robot Experience

- If yes, how many years of experience do you have interacting with robots? (select all applicable)

<table>
<thead>
<tr>
<th></th>
<th>Physical</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>less than a yr in my K 12 school</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>a yr or more in my K 12 school</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>less than a yr in undergrad/grad</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>more than a yr in my undergrad/grad</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>less than a year part of my research</td>
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</tr>
<tr>
<td>more than a yr part of my research</td>
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<td>0</td>
</tr>
<tr>
<td>less than a yr part of job</td>
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</tr>
<tr>
<td>more than a yr part of job</td>
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<td>0</td>
</tr>
<tr>
<td>not applicable</td>
<td>12</td>
<td>23</td>
</tr>
<tr>
<td>num of participants</td>
<td>30</td>
<td>33</td>
</tr>
</tbody>
</table>
D.2 Section I: Agent/Robot Level View

D.2.1 COLLABORATION

- PRE COLLABORATION: I think that I can collaborate successfully with a robot in this treasure hunt game.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>16</td>
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<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>16</td>
<td>7</td>
</tr>
</tbody>
</table>

- Mary (Collaboration) I thought that I collaborated successfully with the Robot Mary in this treasure hunt game.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
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<td>8</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>5</td>
<td>1</td>
<td>6</td>
<td>2</td>
<td>9</td>
<td>5</td>
</tr>
</tbody>
</table>
- **Fiona (Collaboration)** I thought that I collaborated successfully with the Robot Fiona in this treasure hunt game.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
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</thead>
<tbody>
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<td>0</td>
<td>1</td>
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<td>10</td>
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<tr>
<td>SIM-ALL-USERS</td>
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<td>0</td>
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<td>2</td>
<td>5</td>
<td>10</td>
<td>14</td>
</tr>
</tbody>
</table>

- **Collaboration: Successfully collaborated with the Robot**

<table>
<thead>
<tr>
<th></th>
<th>Agreed</th>
<th>Disagreed</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mary (PHYS)</td>
<td>21</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Fiona (PHYS)</td>
<td>27</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Mary (SIM)</td>
<td>19</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>Fiona (SIM)</td>
<td>29</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

**D.2.2 TRUST**

- **PRE (TRUST):** I think that a robot can be a trustworthy collaborator.

<table>
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<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
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<tbody>
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<td>0</td>
<td>0</td>
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<td>0</td>
<td>4</td>
<td>8</td>
<td>11</td>
<td>9</td>
</tr>
</tbody>
</table>
• Mary (TRUST) I thought that Robot Mary was a trustworthy collaborator.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
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</thead>
<tbody>
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<tr>
<td>SIM-ALL-USERS</td>
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<td>6</td>
<td>2</td>
<td>9</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

• Fiona (TRUST) I thought that Robot Fiona was a trustworthy collaborator.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
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<tbody>
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<td>PHYS-ALL-USERS</td>
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<td>0</td>
<td>3</td>
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<td>SIM-ALL-USERS</td>
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<td>3</td>
<td>2</td>
<td>5</td>
<td>9</td>
<td>13</td>
</tr>
</tbody>
</table>

• TRUST: Robot was a trustworthy collaborator

<table>
<thead>
<tr>
<th></th>
<th>Agreed</th>
<th>Disagreed</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mary (PHYS)</td>
<td>21</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Fiona (PHYS)</td>
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<td>0</td>
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<tr>
<td>Mary (SIM)</td>
<td>18</td>
<td>4</td>
<td>11</td>
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<tr>
<td>Fiona (SIM)</td>
<td>27</td>
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</tr>
</tbody>
</table>
D.2.3 COMMUNICATION

- **PRE COMMUNICATION:** I don’t think that I have to expend a lot of effort to communicate with a robot.

<table>
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<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
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<th>disagree</th>
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<td>SIM-ALL-USERS</td>
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<td>4</td>
<td>4</td>
<td>8</td>
<td>12</td>
<td>2</td>
</tr>
</tbody>
</table>

- **Mary (COMMUNICATION)** I didn’t think that I had to expend a lot of effort to communicate with Robot Mary.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
</tr>
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<td>0</td>
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<td>9</td>
<td>6</td>
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<tr>
<td>SIM-ALL-USERS</td>
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<td>1</td>
<td>3</td>
<td>5</td>
<td>6</td>
<td>9</td>
<td>7</td>
</tr>
</tbody>
</table>

- **Fiona (COMMUNICATION)** I didn’t think that I had to expend a lot of effort to communicate with Robot Fiona.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
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<td>2</td>
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<tr>
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<td>0</td>
<td>3</td>
<td>2</td>
<td>5</td>
<td>12</td>
<td>11</td>
</tr>
</tbody>
</table>
• **COMMUNICATION:** I don’t think that I have to expend a lot of effort to communicate with a robot.

<table>
<thead>
<tr>
<th></th>
<th>Agreed</th>
<th>Disagreed</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mary (PHYS)</td>
<td>19</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>Fiona (PHYS)</td>
<td>23</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>Mary (SIM)</td>
<td>22</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>Fiona (SIM)</td>
<td>28</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

**D.2.4 TASK SUCCESS/PERFORMANCE**

• **PRE (TASK SUCCESS/PERFORMANCE)** I think that I can be successful at the Treasure Hunt Game without a robot’s help.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
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</thead>
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<td>PHYS-ALL-USERS</td>
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<td>3</td>
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<td>5</td>
<td>1</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td>11</td>
<td>6</td>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>

• **Mary (TASK SUCCESS/PERFORMANCE)** I thought that I was successful at the Treasure Hunt Game without Robot Mary’s help.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
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</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>3</td>
<td>2</td>
<td>9</td>
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<td>4</td>
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<td>0</td>
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<tr>
<td>SIM-ALL-USERS</td>
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<td>1</td>
<td>7</td>
<td>4</td>
<td>5</td>
<td>9</td>
<td>1</td>
</tr>
</tbody>
</table>
\begin{itemize}
\item \textit{Fiona (TASK SUCCESS/PERFORMANCE)} I thought that I was successful at the Treasure Hunt Game without Robot Fiona’s help.
\end{itemize}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline
 & num of participants & strongly disagree & somewhat disagree & disagree & neither & somewhat agree & strongly agree \\
\hline
PHYS-ALL-USERS & 30 & 3 & 1 & 7 & 2 & 7 & 6 & 4 \\
SIM-ALL-USERS & 33 & 7 & 0 & 10 & 4 & 7 & 4 & 1 \\
\hline
\end{tabular}
\caption{Participants' responses to the question: \textit{I thought that I was successful at the Treasure Hunt Game without Robot’s help.}}
\end{table}

\begin{itemize}
\item \textit{TASK SUCCESS/PERFORMANCE:} I thought that I was successful at the Treasure Hunt Game without Robot’s help.
\end{itemize}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
 & Agreed & Disagreed & Neither \\
\hline
Mary (PHYS) & 11 & 14 & 5 \\
Fiona (PHYS) & 17 & 11 & 2 \\
Mary (SIM) & 15 & 14 & 4 \\
Fiona (SIM) & 12 & 17 & 4 \\
\hline
\end{tabular}
\caption{Participants' responses to the question: \textit{I thought that I was successful at the Treasure Hunt Game without Robot’s help.}}
\end{table}

\section*{D.2.5 USERS VIEW OF COLLABORATION}

\begin{itemize}
\item \textit{PRE (USERS VIEW OF COLLABORATION)} In general, I find it easier to work alone.
\end{itemize}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|c|}
\hline
 & num of participants & strongly disagree & somewhat disagree & disagree & neither & somewhat agree & strongly agree \\
\hline
PHYS-ALL-USERS & 30 & 1 & 2 & 3 & 13 & 5 & 5 & 1 \\
SIM-ALL-USERS & 33 & 0 & 0 & 0 & 4 & 11 & 11 & 7 \\
\hline
\end{tabular}
\caption{Participants' responses to the question: \textit{In general, I find it easier to work alone.}}
\end{table}
• Mary (USERS VIEW OF COLLABORATION) In general, I find it easier to work alone.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
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<td>3</td>
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<td>7</td>
<td>6</td>
<td>4</td>
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</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>5</td>
<td>6</td>
<td>8</td>
<td>5</td>
</tr>
</tbody>
</table>

• Fiona (USERS VIEW OF COLLABORATION) In general, I find it easier to work alone.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
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<th>strongly agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
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<td>3</td>
<td>8</td>
<td>7</td>
<td>6</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
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<td>2</td>
<td>5</td>
<td>5</td>
<td>6</td>
<td>8</td>
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</tbody>
</table>

• USERS VIEW OF COLLABORATION: In general, I find it easier to work alone.

<table>
<thead>
<tr>
<th></th>
<th>Agreed</th>
<th>Disagreed</th>
<th>Neither</th>
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</thead>
<tbody>
<tr>
<td>PRE (PHYS)</td>
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<td>13</td>
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<tr>
<td>Mary (PHYS)</td>
<td>10</td>
<td>13</td>
<td>7</td>
</tr>
<tr>
<td>Fiona (PHYS)</td>
<td>8</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>PRE (SIM)</td>
<td>29</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Mary (SIM)</td>
<td>19</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>Fiona (SIM)</td>
<td>29</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>
D.3  Section II : System/Task Level View

D.3.1  ROBOT EFFORT

- **PRE (ROBOT-EFFORT):** I think that collaborating with a robot will make my task easier than working on the task alone.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>strongly disagree</th>
<th>somewhat disagree</th>
<th>disagree</th>
<th>neither</th>
<th>somewhat agree</th>
<th>agree</th>
<th>strongly agree</th>
</tr>
</thead>
<tbody>
<tr>
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</tbody>
</table>

- **Mary (ROBOT-EFFORT)** I thought that collaborating with Robot Mary made my task easier than working on the task alone.

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
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</tbody>
</table>

- **Fiona (ROBOT-EFFORT)** I thought that collaborating with Robot Fiona made my task easier than working on the task alone.

<table>
<thead>
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<th>num of participants</th>
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</table>
- **ROBOT-EFFORT:** I think that collaborating with a robot made my task easier than working on the task alone.

<table>
<thead>
<tr>
<th></th>
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<th>Disagreed</th>
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<tr>
<td>Mary (PHYS)</td>
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<td>Fiona (PHYS)</td>
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<tr>
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### D.3.2 ROBOT-RELIABILITY-TASK-SUCCESS

- **PRE (ROBOT-RELIABILITY-TASK-SUCCESS):** I think that the robot will provide me with reliable information that will help me succeed in the task.

<table>
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<tr>
<th></th>
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</table>

- **Mary (ROBOT-RELIABILITY-TASK-SUCCESS) I thought that Robot Mary provided me with reliable information that helped me succeed in the task.**

<table>
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<tr>
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<td>7</td>
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<td>6</td>
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</tbody>
</table>
- Fiona (ROBOT-RELIABILITY-TASK-SUCCESS) I thought that Robot Fiona provided me with reliable information that helped me succeed in the task.

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- ROBOT-RELIABILITY-TASK-SUCCESS: I think that the robot provided me with reliable information that will help me succeed in the task.

<table>
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<tr>
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<tr>
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<td>Mary (SIM)</td>
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<td>Fiona (SIM)</td>
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</table>
D.3.3 TASK-COMPLETION

- **PRE (TASK-COMPLETION):** I think that I can complete the task quickly while getting help from the robot.

<table>
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<th></th>
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<td>3</td>
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</table>

- **Mary (TASK COMPLETION)** I thought that I completed the task quickly because I got help from Robot Mary.

<table>
<thead>
<tr>
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<th>num of participants</th>
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- **Fiona (TASK COMPLETION)** I thought that I completed the task quickly because I got help from Robot Fiona.

<table>
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<tr>
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<td>3</td>
<td>8</td>
<td>9</td>
<td>10</td>
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</table>
• **TASK-COMPLETION** I think that I completed the task quickly while getting help from the robot.

<table>
<thead>
<tr>
<th></th>
<th>Agreed</th>
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<td>Mary (SIM)</td>
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<td>Fiona (SIM)</td>
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**D.3.4 FULL DIALOGUE/SYSTEM EFFECT**

• **FULL DIALOGUE/SYSTEM EFFECT**: I trust the robot to catch something I miss while I am making my decision.

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• Mary (**FULL DIALOGUE/SYSTEM EFFECT**) I trusted Robot Mary to catch something I missed while I was making decisions.

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<tr>
<th></th>
<th>num of participants</th>
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<th>disagree</th>
<th>neither</th>
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• **Fiona (FULL DIALOGUE/SYSTEM EFFECT)** I trusted Robot Fiona to catch something I missed while I was making decisions.

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• **FULL DIALOGUE/SYSTEM EFFECT**: I trusted the robot to catch something I miss while I am making my decision.

<table>
<thead>
<tr>
<th></th>
<th>Agreed</th>
<th>Disagreed</th>
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**D.3.5 FULL DIALOGUE/SYSTEM EFFECT**

• **PRE (FULL DIALOGUE/SYSTEM EFFECT)**: I think that discussing with the robot will slow me down to make the decision.

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• Mary (FULL DIALOGUE/SYSTEM EFFECT) I thought that Robot Mary slowed me down to make decisions.

<table>
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• Fiona (FULL DIALOGUE/SYSTEM EFFECT) I thought that Robot Fiona slowed me down to make decisions.

<table>
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• FULL DIALOGUE/SYSTEM EFFECT: I think that discussing with the robot slowed me down to make the decision.

<table>
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D.4 Section III

*Section III (Only appears in POST survey after interacting with both minimal and full dialogue mode)*

1. **TASK COMPLEXITY: How difficult was each scenario to understand?**

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<tr>
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2. **Given a SIMPLE task, I prefer Mary or Fiona.**

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<th>Fiona</th>
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3. Given a COMPLEX task, I prefer Mary or Fiona.

<table>
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</thead>
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4. How well would you say you understood the task while interacting with Robot Mary that did not provide any feedback?

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<table>
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</tbody>
</table>

5. How well would you say you understood the task while interacting with Robot Fiona that provided feedback?

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>very poor</th>
<th>somewhat poor</th>
<th>poor</th>
<th>neither</th>
<th>somewhat well</th>
<th>well</th>
<th>very well</th>
</tr>
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<tbody>
<tr>
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<td>30</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>7</td>
<td>19</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>3</td>
<td>9</td>
<td>19</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Well</th>
<th>Poor</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1</td>
</tr>
<tr>
<td>SIM</td>
<td>31</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>
6. **How much did the Robot Fiona’s feedback help you resolve problems?**

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>not helpful at all</th>
<th>somewhat not helpful</th>
<th>not helpful</th>
<th>neither</th>
<th>somewhat helpful</th>
<th>helpful</th>
<th>very helpful</th>
</tr>
</thead>
<tbody>
<tr>
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<td>30</td>
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<td>2</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>10</td>
<td>13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Helpful</th>
<th>Not Helpful</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
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</tr>
<tr>
<td>SIM</td>
<td>27</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>
7. How mentally demanding was the task while interacting with Robot Mary that did not provide any feedback?

<table>
<thead>
<tr>
<th></th>
<th>num of part.</th>
<th>not demanding at all</th>
<th>somewhat not demanding</th>
<th>demanding</th>
<th>neither</th>
<th>somewhat demand.</th>
<th>demand.</th>
<th>very demand.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>7</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>5</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>7</td>
<td>5</td>
<td>3</td>
<td>6</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Demanding</th>
<th>Not Demanding</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>7</td>
<td>15</td>
<td>6</td>
</tr>
<tr>
<td>SIM</td>
<td>12</td>
<td>15</td>
<td>6</td>
</tr>
</tbody>
</table>

8. How mentally demanding was the task while interacting with Robot Fiona that provided feedback?

<table>
<thead>
<tr>
<th></th>
<th>num of part.</th>
<th>not demanding at all</th>
<th>somewhat not demanding</th>
<th>demanding</th>
<th>neither</th>
<th>somewhat demand.</th>
<th>demand.</th>
<th>very demand.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>30</td>
<td>8</td>
<td>6</td>
<td>7</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>7</td>
<td>5</td>
<td>2</td>
<td>8</td>
<td>4</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Demanding</th>
<th>Not Demanding</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>6</td>
<td>21</td>
<td>3</td>
</tr>
<tr>
<td>SIM</td>
<td>11</td>
<td>14</td>
<td>8</td>
</tr>
</tbody>
</table>
9. *How hard was it to make a decision (or come up with a plan to solve the game)*

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>very easy</th>
<th>somewhat easy</th>
<th>easy</th>
<th>neither</th>
<th>somewhat difficult</th>
<th>difficult</th>
<th>very difficult</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>6</td>
<td>5</td>
<td>8</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>7</td>
<td>4</td>
<td>2</td>
<td>7</td>
<td>9</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Difficult</th>
<th>Easy</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>7</td>
<td>19</td>
<td>4</td>
</tr>
<tr>
<td>SIM</td>
<td>13</td>
<td>13</td>
<td>7</td>
</tr>
</tbody>
</table>

10. *How much did the Robot Fiona’s feedback help your decision making?*

<table>
<thead>
<tr>
<th></th>
<th>num of participants</th>
<th>not helpful at all</th>
<th>somewhat not helpful</th>
<th>not helpful</th>
<th>neither</th>
<th>somewhat helpful</th>
<th>helpful</th>
<th>very helpful</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>9</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>11</td>
<td>4</td>
<td>14</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Helpful</th>
<th>Not Helpful</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS</td>
<td>23</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>SIM</td>
<td>29</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>
D.5 HRTeam Data Analysis

- Physical Experiment

<table>
<thead>
<tr>
<th></th>
<th>Execution Time</th>
<th>Total Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Dialogue</td>
<td>217.6378528</td>
<td>1855.5384426</td>
</tr>
<tr>
<td>Min Dialogue</td>
<td>307.6676064</td>
<td>2303.003881</td>
</tr>
</tbody>
</table>

![Distance Traveled](image1)

Figure D.1: Live Experiment: Total Distance Traveled

![Execution Time](image2)

Figure D.2: Live Experiment: Total Execution Time
• Simulation Experiment

<table>
<thead>
<tr>
<th></th>
<th>Execution Time</th>
<th>Total Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Dialogue</td>
<td>434.3929923</td>
<td>1378.212916</td>
</tr>
<tr>
<td>Min Dialogue</td>
<td>611.4480225</td>
<td>1947.551272</td>
</tr>
</tbody>
</table>

Figure D.3: Simulation Experiment: Total Distance Traveled

Figure D.4: Simulation Experiment: Total Execution Time

D.5.1 Trajectory Logs
Table D.2: Robot Trajectory Logs from Physical Experiment (User 1-User 10). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary
Table D.3: Robot Trajectory Logs from Physical Experiment (User 11- User 20). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>D2</td>
<td>ND1</td>
<td>D1</td>
<td>ND2</td>
<td>D2</td>
<td>ND1</td>
<td>D1</td>
<td>ND2</td>
<td>D2</td>
<td>ND1</td>
<td>D1</td>
<td>ND2</td>
<td>D2</td>
<td>ND1</td>
<td>D1</td>
<td>ND2</td>
<td>D2</td>
<td>ND1</td>
<td>D1</td>
<td>ND2</td>
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</tbody>
</table>

243
Table D.4: Robot Trajectory Logs from Physical Experiment (User 21-User 30). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary

<table>
<thead>
<tr>
<th>User</th>
<th>Dialogue Type</th>
<th>User</th>
<th>Dialogue Type</th>
<th>User</th>
<th>Dialogue Type</th>
<th>User</th>
<th>Dialogue Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>D2</td>
<td>21</td>
<td>ND1</td>
<td>22</td>
<td>D1</td>
<td>22</td>
<td>ND2</td>
</tr>
<tr>
<td>23</td>
<td>D2</td>
<td>23</td>
<td>ND1</td>
<td>24</td>
<td>D1</td>
<td>24</td>
<td>ND2</td>
</tr>
<tr>
<td>25</td>
<td>D2</td>
<td>25</td>
<td>ND1</td>
<td>26</td>
<td>D1</td>
<td>26</td>
<td>ND2</td>
</tr>
<tr>
<td>28</td>
<td>D2</td>
<td>28</td>
<td>ND1</td>
<td>30</td>
<td>D2</td>
<td>30</td>
<td>ND1</td>
</tr>
</tbody>
</table>
Table D.5: Robot Trajectory Logs from Simulation Experiment (User 1-User 10). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary

<table>
<thead>
<tr>
<th>User</th>
<th>D1</th>
<th>ND2</th>
<th>D2</th>
<th>ND1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
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</tr>
<tr>
<td>10</td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table D.6: Robot Trajectory Logs from Simulation Experiment (User 11-User 20). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary

user 11:D1  user 11:ND2  user 12:D2  user 12:ND1

user 13:D1  user 13:ND2  user 14:D2  user 14:ND1

user 15:D1  user 15:ND2  user 16:D2  user 16:ND1

user 17:D1  user 17:ND2  user 18:D2  user 18:ND1

user 19:D1  user 19:ND2  user 20:D2  user 20:ND1

246
Table D.7: Robot Trajectory Logs from Simulation Experiment (User 11-User 20). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary

<table>
<thead>
<tr>
<th>User</th>
<th>D1</th>
<th>ND2</th>
<th>D2</th>
<th>ND1</th>
</tr>
</thead>
<tbody>
<tr>
<td>user 21</td>
<td><img src="user_21_d1.png" alt="Image" /></td>
<td><img src="user_21_nd2.png" alt="Image" /></td>
<td><img src="user_22_d2.png" alt="Image" /></td>
<td><img src="user_22_nd1.png" alt="Image" /></td>
</tr>
<tr>
<td>user 22</td>
<td><img src="user_23_d1.png" alt="Image" /></td>
<td><img src="user_23_nd2.png" alt="Image" /></td>
<td><img src="user_24_d2.png" alt="Image" /></td>
<td><img src="user_24_nd1.png" alt="Image" /></td>
</tr>
<tr>
<td>user 23</td>
<td><img src="user_25_d1.png" alt="Image" /></td>
<td><img src="user_25_nd2.png" alt="Image" /></td>
<td><img src="user_26_d2.png" alt="Image" /></td>
<td><img src="user_26_nd1.png" alt="Image" /></td>
</tr>
<tr>
<td>user 24</td>
<td><img src="user_27_d1.png" alt="Image" /></td>
<td><img src="user_27_nd2.png" alt="Image" /></td>
<td><img src="user_28_d2.png" alt="Image" /></td>
<td><img src="user_28_nd1.png" alt="Image" /></td>
</tr>
<tr>
<td>user 25</td>
<td><img src="user_29_d1.png" alt="Image" /></td>
<td><img src="user_29_nd2.png" alt="Image" /></td>
<td><img src="user_30_d2.png" alt="Image" /></td>
<td><img src="user_30_nd1.png" alt="Image" /></td>
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</tbody>
</table>

247
Table D.8: Robot Trajectory Logs from Simulation Experiment (User 31-User 33). D1=Full Dialogue first with Robot Fiona; ND1= Minimal Dialogue first with Robot Mary; D2=Full Dialogue second with Robot Fiona; ND2= Minimal Dialogue second with Robot Mary

<table>
<thead>
<tr>
<th>User</th>
<th>Dialogue Type</th>
</tr>
</thead>
<tbody>
<tr>
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<td>D1</td>
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<tr>
<td>31</td>
<td>ND2</td>
</tr>
<tr>
<td>32</td>
<td>D2</td>
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<td>32</td>
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<tr>
<td>33</td>
<td>D1</td>
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<tr>
<td>33</td>
<td>ND2</td>
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</tbody>
</table>
### D.6 Dialogue Analysis

<table>
<thead>
<tr>
<th></th>
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<th>ArgDialogue</th>
<th>%</th>
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</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td></td>
<td>9</td>
<td>21</td>
<td>70%</td>
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<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
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<td>6</td>
<td>27</td>
<td>82%</td>
</tr>
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</table>

Table D.9: Argumentation-based Dialogues triggered during *where to go* discussion

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>ArgDial</th>
<th>Total%</th>
<th>Ch</th>
<th>ArgDial%</th>
<th>Acc</th>
<th>ArgDial%</th>
<th>Rej</th>
<th>ArgDial%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>21</td>
<td>70%</td>
<td>15</td>
<td>71%</td>
<td>19</td>
<td>90%</td>
<td>2</td>
<td>10%</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>27</td>
<td>82%</td>
<td>16</td>
<td>59%</td>
<td>25</td>
<td>93%</td>
<td>2</td>
<td>7%</td>
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</tbody>
</table>

Table D.10: Argumentation-based Dialogues triggered during *where to go* discussion where Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>No Dialogue (Agreement)</th>
<th>%</th>
<th>ArgDialogue</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td></td>
<td>12</td>
<td>18</td>
<td>60%</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td></td>
<td>11</td>
<td>22</td>
<td>67%</td>
</tr>
</tbody>
</table>

Table D.11: Argumentation-based Dialogues triggered during *how to get there* discussion
<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>ArgDial</th>
<th>Total%</th>
<th>Ch</th>
<th>ArgDial%</th>
<th>Acc</th>
<th>ArgDial%</th>
<th>Rej</th>
<th>ArgDial%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>30</td>
<td>18</td>
<td>60%</td>
<td>9</td>
<td>50%</td>
<td>12</td>
<td>67%</td>
<td>2</td>
<td>11%</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>33</td>
<td>22</td>
<td>67%</td>
<td>13</td>
<td>59%</td>
<td>17</td>
<td>77%</td>
<td>5</td>
<td>23%</td>
</tr>
</tbody>
</table>

Table D.12: Argumentation-based Dialogues triggered during **how to get there** discussion where Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

<table>
<thead>
<tr>
<th></th>
<th>Total ArgDial</th>
<th>Ch</th>
<th>ArgDial%</th>
<th>Acc</th>
<th>ArgDial%</th>
<th>Rej</th>
<th>ArgDial%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL-USERS</td>
<td>121</td>
<td>20</td>
<td>17%</td>
<td>107</td>
<td>88%</td>
<td>14</td>
<td>12%</td>
</tr>
<tr>
<td>SIM-ALL-USERS</td>
<td>121</td>
<td>25</td>
<td>21%</td>
<td>107</td>
<td>88%</td>
<td>14</td>
<td>12%</td>
</tr>
</tbody>
</table>

Table D.13: Argumentation-based Dialogues triggered during **what is found there** discussion where Ch= ArgHRI Dialogue was challenged either by human collaborator or robot Fiona, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

<table>
<thead>
<tr>
<th></th>
<th>Total Persuasion Dialogue</th>
<th>Challenges</th>
<th>Ch%</th>
<th>Accept</th>
<th>Acc%</th>
<th>Reject</th>
<th>Rej%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL</td>
<td>11</td>
<td>7</td>
<td>64%</td>
<td>9</td>
<td>82%</td>
<td>2</td>
<td>18%</td>
</tr>
<tr>
<td>SIM-ALL</td>
<td>16</td>
<td>10</td>
<td>63%</td>
<td>14</td>
<td>88%</td>
<td>2</td>
<td>13%</td>
</tr>
</tbody>
</table>

Table D.14: Argumentation-based Persuasion Dialogues (R2H) triggered during **where to go** discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

<table>
<thead>
<tr>
<th></th>
<th>Total InfoSeek Dialogue</th>
<th>Challenges</th>
<th>Ch%</th>
<th>Accept</th>
<th>Acc%</th>
<th>Reject</th>
<th>Rej%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL</td>
<td>7</td>
<td>6</td>
<td>86%</td>
<td>7</td>
<td>100%</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>SIM-ALL</td>
<td>11</td>
<td>6</td>
<td>55%</td>
<td>11</td>
<td>100%</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

Table D.15: Argumentation-based InfoSeek Dialogues (H2R) triggered during **where to go** discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement

<table>
<thead>
<tr>
<th></th>
<th>Total Persuasion Dialogue</th>
<th>Challenges</th>
<th>Ch%</th>
<th>Accept</th>
<th>Acc%</th>
<th>Reject</th>
<th>Rej%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL</td>
<td>12</td>
<td>8</td>
<td>67%</td>
<td>10</td>
<td>83%</td>
<td>2</td>
<td>17%</td>
</tr>
<tr>
<td>SIM-ALL</td>
<td>20</td>
<td>12</td>
<td>60%</td>
<td>15</td>
<td>75%</td>
<td>5</td>
<td>25%</td>
</tr>
</tbody>
</table>

Table D.16: Argumentation-based Persuasion Dialogues (R2H) triggered during **how to go there** discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement
<table>
<thead>
<tr>
<th>Total InfoSeek Dialogue</th>
<th>Challenges</th>
<th>Ch%</th>
<th>Accept</th>
<th>Acc%</th>
<th>Reject</th>
<th>Rej%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHYS-ALL</td>
<td>6</td>
<td>1</td>
<td>17%</td>
<td>6</td>
<td>100%</td>
<td>0</td>
</tr>
<tr>
<td>SIM-ALL</td>
<td>2</td>
<td>1</td>
<td>50%</td>
<td>2</td>
<td>100%</td>
<td>0</td>
</tr>
</tbody>
</table>

Table D.17: Argumentation-based InfoSeek Dialogues (H2R) triggered during how to get there? discussion where Ch= ArgHRI Dialogue challenged by human collaborator, Acc=ArgHRI Dialogue ends with agreement, Rej=ArgHRI Dialogue ends with disagreement
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