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Evaluating Human-robot Implicit Communication Through Human-human Implicit Communication

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EVALUATING HUMAN-ROBOT IMPLICIT COMMUNICATION THROUGH HUMAN-HUMAN IMPLICIT COMMUNICATION

by

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“None of it was acting,” said Captain Malich. “All I did was permit it to be seen.”

Empire, Orson Scott Card

ABSTRACT

Human-Robot Interaction (HRI) research is examining ways to make human-robot (HR) communication more natural. Incorporating natural communication techniques is expected to make HR communication seamless and more natural for humans. Humans naturally incorporate implicit levels of communication, and including implicit communication in HR communication should provide tremendous benefit. The aim for this work was to evaluate a model for human-robot implicit communication. Specifically, the primary goal for this research was to determine whether humans can assign meanings to implicit cues received from autonomous robots as they do for identical implicit cues received from humans.

An experiment was designed to allow participants to assign meanings to identical, implicit cues (pursuing, retreating, investigating, hiding, patrolling) received from humans and robots. Participants were tasked to view random video clips of both entity types, label the implicit cue, and assign a level of confidence in their chosen answer. Physiological data was tracked during the experiment using an electroencephalogram and eye-tracker. Participants answered workload and stress measure questionnaires following each scenario.

Results revealed that participants were significantly more accurate with human cues (84%) than with robot cues (82%), however participants were highly accurate, above 80%, for both entity types. Despite the high accuracy for both types, participants remained significantly more confident in answers for humans (6.1) than for robots (5.9) on a confidence scale of 1 - 7.

Subjective measures showed no significant differences for stress or mental workload across entities. Physiological measures were not significant for the engagement index across

entity, but robots resulted in significantly higher levels of cognitive workload for participants via the index of cognitive activity.

The results of this study revealed that participants are more confident interpreting human implicit cues than identical cues received from a robot. However, the accuracy of interpreting both entities remained high. Participants showed no significant difference in interpreting different cues across entity as well. Therefore, much of the ability of interpreting an implicit cue resides in the actual cue rather than the entity. Proper training should boost confidence as humans begin to work alongside autonomous robots as teammates, and it is possible to train humans to recognize cues based on the movement, regardless of the entity demonstrating the movement.

1 Peter 5:10

This work is dedicated to Team Richardson

who have continually put family first

throughout all of our travels.

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LIST OF ACRONYMNS/ABBREVIATIONS

AI	Artificial Intelligence
BIC	Behavioral Implicit Communication
CMM	Coordinated Management of Meaning
DoD	Department of Defense
DSSQ	Dundee Stress State Questionnaire
ECG	Electrocardiogram
EEG	Electroencephalogram
EOD	Explosive Ordnance Disposal
FCS	Future Combat Systems
HDAMCT	The Headquarters Department of the Army's Manual of Common Tasks
HR	Human Robot
HRI	Human Robot Interaction
ICA	Index of Cognitive Activity
MII	Mixed Initiative Interaction
NASA-TLX	NASA Task Load Index
NNI	Nearest Neighbor Index
P2P	Peer-to-Peer
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
USR	Urban Search and Rescue

CHAPTER ONE: GENERAL INTRODUCTION

In the 1977 film, *Star Wars*, George Lucas captivated audiences by introducing a fictional realm in which humans coexisted with completely autonomous robots. Although the robots in the film were subordinate to humans, they were treated as peers and cooperated with characters in the film in social and support roles. Robots aided humans during decision-making, flight navigation, and foreign language interpretation. Thirty-five years later, an actual robot that is completely autonomous might still be considered fictional, yet much work is underway to make Lucas' vision a modern reality.

Researchers are working to bridge the gap between the *Star Wars* universe and our own. Current robotic advances include Leonardo, a highly expressive robot designed to interact with humans in a social manner (Breazeal, Kidd, Thomaz, Hoffman & Berlin, 2005), and BigDog, a robot designed to carry heavy equipment across rough terrain (Raibert, Blankespoor, Nelson, Playter & the BigDog Team, 2008). However, researchers today are faced with many of the same challenges encountered by the characters of the *Star Wars* movies. Anakin Skywalker found intricacies in building C3PO, such as sensors, intelligence, and interactions, and Luke Skywalker discovered complications in terms of proper functioning and cooperation, in fixing a newly bought droid named R2D2.

As a result of such complexities, several sub-disciplines exist within the robotics field. One addresses artificial intelligence (AI), which Luger and Stubblefield (1989) defined as science concerned with the automation of intelligent behavior. Another is dexterous mobility and manipulation, which focus on designing robots with the ability to rotate the body and reach reference points near the body (Haug, Adkins & Cororian, 1998). A third is perception, which aims to increase a robot's ability to recognize environmental stimuli (color, distance, movement) based on internal sensors (Steinfeld, Fong, Kaber, Lewis, Scholtz & Schultz, 2006). Finally, human-robot interaction (HRI) addresses the ways in which humans and robots influence each other (Fong, Thorpe & Baur, 2003).

The ultimate goal for robotics is to design and develop an autonomous robot capable of acting as a teammate. This implies that the current state-of-the-art for a robot is use as a tool, requiring direct control by a human, oftentimes increasing workload and stress depending on the roles or number of robots being utilized (Prewett, Johnson, Saboe, Elliott & Coovert, 2010). Also, controlling a robot directly requires a dedicated human operator, thus decreasing the number of tasks completed simultaneously and often diminishing situation awareness (Prewett et al., 2006). Even with these limitations, the use of robots reduces cost in terms of finances and safety, especially in high-risk environments such as urban search and rescue (USR; Baker & Vanco, 2004; Burke, Murphy, Coovert & Riddle, 2004; Drury, Scholtz & Yanco, 2004; Scholtz, Young & Drury, 2004) and explosive ordnance disposal (EOD). Robots aid humans in USR by easily maneuvering through areas that are difficult for humans to navigate, or are hazardous due to falling debris or unstable, damaged structures (Murphy, 2004). Robots are beneficial in EOD because they are more resilient than humans conducting the same task. For example, robots are not psychologically distracted or stressed, and can absorb damage more readily than humans (Barnes & Evans, 2010; Fielding, 2006; Montgomery, 2005). In addition, replacing a lost robotic leg, sensor, or damaged processor, allows robots the opportunity to return to the team more often than humans suffering similar damage.

It is evident that the benefits yielded from robots, even as direct-control tools, are substantial. The alternative is not having robots at all, which would significantly increase cost in terms of money and safety for conducting many operations particular to the military or other armed government agencies. To illustrate, unlike a robot that is able to return to a team once a sensor is replaced, humans experiencing “equivalent” loss have a lesser chance of returning to duty.

Recognizing the advantages offered by using robots as tools versus not having robots available at all is an important step in the progress of HRI. However, in order to shift this paradigm to that of creating human-robot (HR) teams, each sub-discipline of robotics must address specific challenges. The HRI sub-discipline needs to address topics including culture, shared mental models, trust, and communication. Of those problem areas, the methods and means for communicating between human and robot are central. Lewis and Wang (2010) argued that the performance of HR teams is affected by the quality of their communication. Communication, though, is multi-faceted. Each culture has a set of social norms for interacting and those norms shape mental models shared by the people prescribing to those parameters for communicating. A relationship is required to have the concept of trust present and relationships are built upon communication. For the purposes of the present effort, communication is investigated from a multi-modal perspective with emphasis given to implicit communication.

Mutlu, Yamaoka, Kanda, Ishiguro and Hagita (2009) suggested that implicit communication plays a vital role in relationships. In order to optimize the interactions between humans and robots, implicit communication must be explored as a viable aspect of team communication. Castelfranchi (2009) stated that relationships between humans and robots should exist such that both parties understand each other's goals, plans, actions, and assumptions autonomously without explicit communication. Fong (2005) pressed for researchers to develop techniques so that robots will be able to make use of implicit language and gesturing. These examples demonstrate that researchers are clamoring for robots to gain additional modalities for the benefit of working with humans already experienced in multi-modal communication.

Implicit communication is key because it adds clarity and robustness to messages (Adams, Rani & Sarkar, 2004), aids teams in performing tasks more quickly (Blickensderfer, Reynolds, Salas & Cannon-Bowers, 2010), and enhances performance of teams over those using only explicit interaction (Greenstein & Revesman, 1986). Incorporating implicit modalities into HRI is expected to benefit communication among HR teams just as it does human teams.

To concretely understand the importance of implicit communication to the successful development of HR teams, it is necessary to describe in more detail the theoretical underpinnings of implicit communication. Specifically, the present experiment is rooted in the history of HRI and is derived from communication theory.

CHAPTER TWO: REVIEW OF THE LITERATURE

Human Communication Theory

Several definitions of communication exist. Some defined communication as a process (Carey, 1989; Miller, 2002). Others proposed that it is impossible to not communicate and all action is communication (Montagu & Matson, 1979; Wood, 2000). Leeds-Hurwitz (1989) added that communication is action with a pattern. Nonetheless, the bulk of communication definitions involve a message, a sender, and a receiver. The integrated communication model (Figure 1) supports this notion and shows communication flowing to and from communicators. The model highlights a perception filter through which messages pass in order to be encoded/decoded by communicators. Ultimately, the model shows that messages are transmitted via channels.

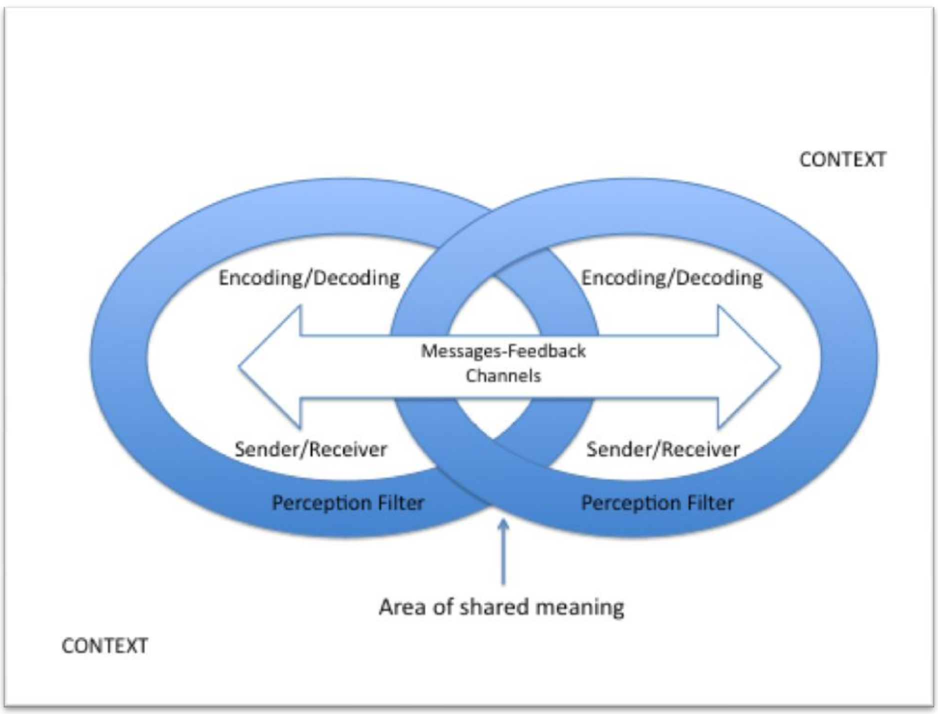

Figure 1: Integrated Communication Model (adapted from http://www.infofanz.com/2009/01/29/the-business-communication-1/)

Communication channels are routes by which communication travels (Mehmood, 2009), or the method a sender employs to send a message (Stone, Singletary & Richmond, 1999). Montagu and Matson (1979) described communication as multidimensional, allowing a sender to choose a variety of channels to convey a message. The authors mentioned three available channels—the auditory-acoustic channel (paralanguage, linguistics), the kinesthetic-visual channel (kinesics, proxemics, gestures, postures), and the tactile channel (touch, feel). Ruben and Stewart (1998) discussed additional channels such as the chronemics channel, in which time or timeliness is used to convey a message, and the appearance-attractiveness channel that uses exterior characteristics such as dress, physique, hair, or adornment to communicate a message. Montagu and Matson (1979) credited Ray Birdwhistell as the founder of multichannel communication models since prior to his 1952 book, *Introduction to Kinesics*, many viewed communication as only explicit, auditory messages.

A *communication strategy* is the way in which a communicator chooses to share information (Wood, 1976). Communication strategies consist of using the appropriate channel for the appropriate situation. Examples of communication strategies include choosing the appropriate volume while in a theatre, tone when expressing sarcasm or seriousness, or touch while flirting or comforting. Humans learn to utilize the appropriate channel(s) through experience (Lucas, 2008).

Wood (1976) supported this idea with an example of a child whose initial communication strategy is to reach for items of interest. At this stage, the child is unknowingly employing *action language*. At the next stage, the child may reach for the item while saying the word “mine”. At this point action language and verbal communication support the child’s desire to attain the item.

Next, a more mature communicator learns to ask and reach toward the object while making a facial expression to denote the mood behind the request (anger, urgency, joy). Ultimately, the child will have several communication modalities at his/her disposal—gestures, glances, verbal communication, and facial expressions.

Regardless of the channel used, the message must pass through a perception filter and be decoded/encoded in order to be effective. Effective message perception results from the sender/receiver's understanding of the meaning of a particular message (Mehmood, 2009), and relies upon the perception of both the message and the source. Message perception, the focus of this study, is hindered by puzzling messages (meaning), absence of receiver schema (mental model), absence of redundancy (multimodality), and earlier experiences, assumptions, or biases (culture) (Stone et al., 1999). Communication is therefore made more effective by evaluating one or more of four aspects of the communication environment—meaning, multimodality, mental models, and culture. This research effort focuses on multimodality.

Multimodal Communication

Communication involves sharing messages (Messer, 1994) that can exist as external data such as directions, facts, events, or procedures; or internal data such as experiences, ideas, feelings, goals, intentions, or expectations (Blickensderfer et al., 2010; Tronick, 1989; Wood, 1976). Since messages can be internal or external, communication can occur via various means. Types of communication modalities include gaze, expressions, posture, speech, tone, rate, mood, gestures, and cultural norms. Multiple modes of communication can enhance the robustness of message transmission and reception by unintentionally, yet accurately, supporting the nature of the message. Several aspects of communication are controlled subconsciously, so at times it is out of the hands of the communicator to alter such behavior. Nor should the communicator want to control these modalities, unless based on context, as these modalities aid to accurately enhance the message of the communicator (Kress & Van Leeuwen, 2001). Although humans tend to prefer unimodal communication, multimodal communication has shown to be more effective (Kress & Van Leeuwen, 2001).

Messages can be misinterpreted in situations where multiple modalities are limited (i.e. phone conversations, emails, letters, or texting). As a result, communication support devices, such as emoticons (smiley faces, LOL, or j/k for just kidding), are added in order to counteract the lack of supporting cues (Derks, Bos & Von Grumbkow, 2007; Rezabek & Cochenour, 1998; Walther & D'Addario, 2001). Supporting cues are the communicator's attempt to ensure that the receiver accurately understands the nature of the message. Derks and his associates (2007) found that using emoticons enhanced the intensity of the message by revealing the true tone that inspired the message. Rezabek and Cochenour (1998) wrote that messages written with text alone lack the overt and subtle undertones integrated with visual communication. Consequently, both senders and receivers of the typed messages understand that text lacks the fullness of visual, verbal communication. This example highlights the two-sided nature of communication, which works best when messages are received based on the intent by which they were sent. Ultimately, this discussion is not to support the use of emoticons, nor to argue that visual, verbal communication is superior to written communication, but rather to reinforce the notion that a single mode of communication lacks the communicative strength of several modalities in concert.

The example above refers to the intentional use of communication modalities. Wood (1976) explained that expertise in using communication strategies comes with experience, and that some strategies can be developed unintentionally as parties have more experience interacting. The increase in experience amongst communicators leads to the development of *unintentional* communication strategies (Messer, 1994). The addition of unintentional communication strategies (Figure 2 on page 10) increases the number of communication modalities at the communicator's disposal, resulting in an increased use of implicit communications. Wood (1976) explained that as a communicator matures, their ability to select appropriate strategies becomes second nature, and that appropriate communication strategies improve communication power.

Communication power is the ability to choose, intentionally or unintentionally, the best communication options to accomplish communication goals, which results in communicating effectively and efficiently (Wood, 1976). Effective communication results when the communicator conveys a message in such a way that the receiver has an improved chance of understanding the nature, intent, and meaning of the message. Lackey, Barber, Reinerman, Badler & Hudson (2011) echoed the importance of selecting appropriate communication tactics by defining multi-modal communication as the exchange of information through a *flexible selection of explicit and implicit modalities* that enables interactions and influences behaviors, thoughts, and emotions.

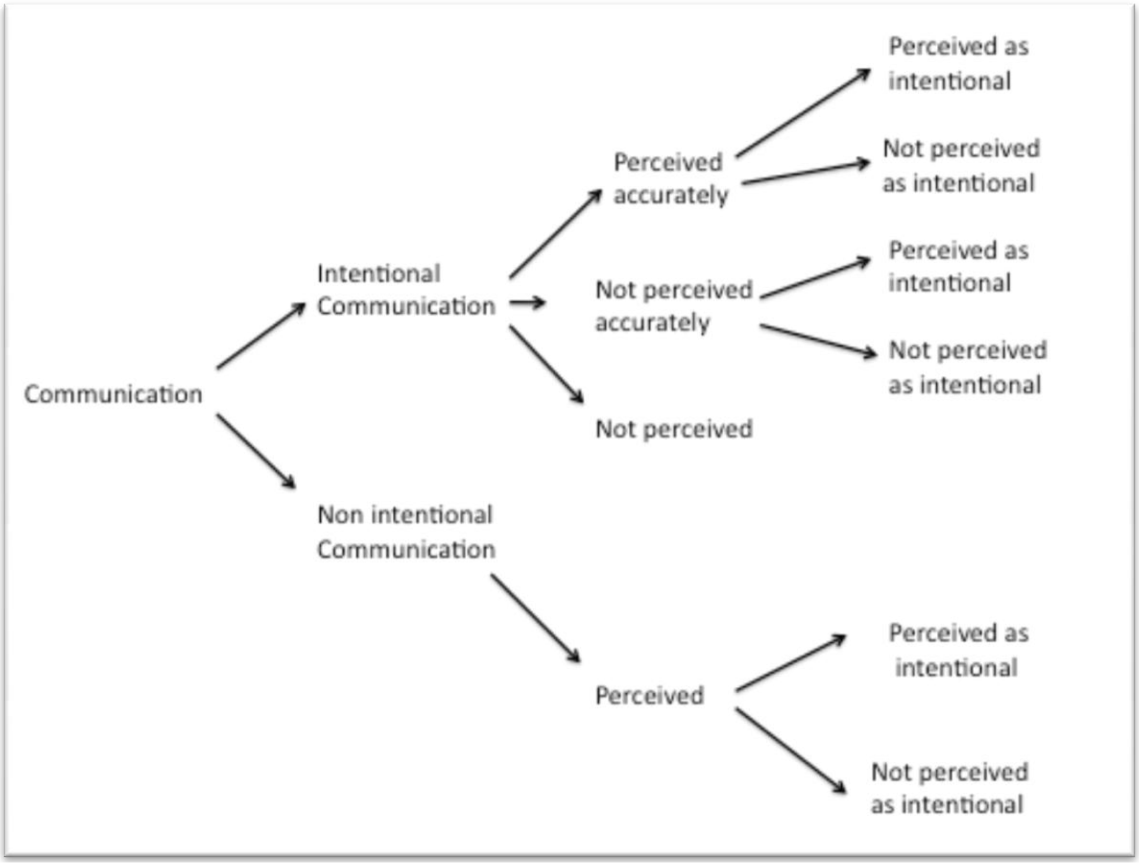

Figure 2: Diagram of the Process of Communication (adapted from Messer, 1994)

Whether multi-modal communication is intentional or unintentional, it aids to add redundancy to messages. Stone et al. (1999) describe redundancy as being important because it gives the receiver multiple chances to properly interpret the message. Noise interrupts communication and redundancy provides additional opportunities for the receiver to acquire the message. Stone et al. (1999) call for repeating messages via the same channel as effective redundancy. Humans naturally build in redundancy via multiple modalities by using implicit communication (Kress & Van Leeuwen, 2001).

Implicit Communication

Communication modalities benefit communication power by increasing the opportunities for the use of implicit communication. There is ubiquitous research demonstrating implicit communication enhancing communication and team performance (Adams et al., 2004; Blickensderfer et al., 2010; Greenstein & Revesman, 1986; Pagello, 1999; Rani, 2006). Communication limited to explicit modalities lengthens message transmission and leaves room for error (Mehrabian, 1981). As in the example discussed previously, humans learn to use several different communication modalities as they grow from children to adults. Even at maturity, humans never lose the use of their initial communication channel—action language. The continued use of this modality, although oftentimes unintentional, strengthens the communication message by adding redundancy.

Implicit communication adds fullness to explicit communication thereby enhancing the quality and *perceive-ability* of the message by supplementing the message with additional modalities (Wilson, 2006). Implicit modalities such as gestures and facial expressions, offer the receiver opportunities to interpret multi-channel messages from any channel uninterrupted by noise. The benefits of implicit communication in team communication have been documented as reducing communication and coordination overhead (Entin & Serfaty, 1999); providing information to indirectly guide teammates' actions when explicit communication is unavailable (Serfaty et al., 1993; Shah and Breazeal, 2010), and aiding teams to achieve communication goals more quickly (Carston, 2009).

Communication based on the explicit modality alone, lacks the robustness associated with natural explicit and implicit communication (Adams et al., 2004). So just as those who communicate via text discover, the deliberate conveyance of information can be misunderstood unless the message includes supporting segments of information that make up for the lack of implicit modalities. Adding these extra layers delays and lengthens the communication process, which undermines the purpose for communicating by text. The additional layers are included to make up for implicit cues, yet since they are purposefully included, they in fact become additional layers of explicit communication.

Lackey et al. (2011) defined implicit communication as the *inadvertent* conveying of information about a team member's behavior patterns and thought processes that will affect interpretation, behaviors, and actions in response to *observed* cues. Although inadvertent, implicit communications have certain advantages over explicit communications, making it beneficial for teams operating in high stress environments. These benefits greatly aid any military unit communicating silently, in harm's way, or with damaged communication devices. Damaged or incomplete communication in military operations is highly likely, yet implicit communication allows subordinate units to take initiative and complete tasks often without words (Wilson, 2006). If communication must be truncated, implicit modalities are beneficial because of their ability to reduce the communication footprint, allowing for enhanced military operations. Mehrabian (1981) argued that explicit communication could be reduced when implicit communication is available. These arguments support the idea that the more recognizable a robotic teammate's behavior is implicitly, the better for human cognition.

Matari (1995) found that implicit behavior speaks to a communicator's own goals. By understanding each other's goals, implicit communication allows communicators to bypass lengthy explicit communication and establish a direct link to each other's minds (Figure 3).

Goals of communication are quickly obtained when interactants imply more and explicitly convey less (Carston, 2009). Under this notion, teammates are free to execute their assigned

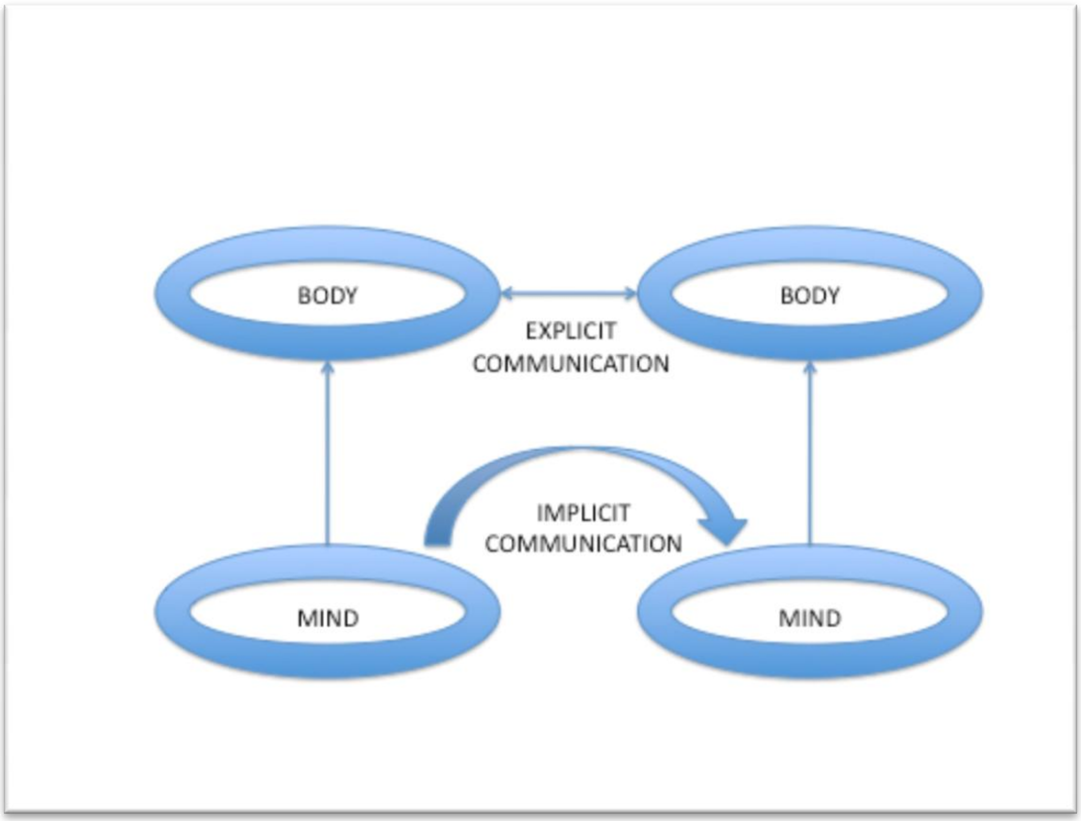

Figure 3: Implicit Communication Bypass Model (adapted from Ingalls, 1981)

tasks that support the team's goals, allowing other team members to read and react to their behavior appropriately (Wilson, 2006). Implicit communication is the information that can be gathered by merely observing the environment, and relies on the perceptual capabilities of the observer (Martins & Demiris, n.d.). Humans use action language in place of explicit communication (to include verbal and/or non-verbal) while interacting (Castelfranchi & Giardini, 2003). Humans are accustomed to complex communication strategies, and effective interactions should include a combination of implicit and explicit modalities such as actions, behavior, gestures, and expressions in order to create robust communication (Giardini &

Castelfranchi, 2004). By using practical actions, the need to communicate with explicit actions and symbols is eliminated. Then, communicators are able to accomplish two goals at once by acting and communicating simultaneously. Deliberate communication is not as critical as implicit communication when it comes to communication robustness for team performance (Balch & Arkin, 1994).

Action Language

Behavioral implicit communication (BIC) is the process of using practical actions as the communicated message (Castelfranchi & Giardini, 2003; Giardini & Castelfranchi, 2004; Castelfranchi, 2009). Castelfranchi and Giardini (2003) explained that humans use action language in place of explicit communication (to include verbal and/or non-verbal) while interacting. By using practical actions, the need to communicate with explicit actions and symbols is eliminated. Then, communicators are able to accomplish two goals at once by acting and communicating simultaneously.

Any BIC is based on the perception of an action (Castelfranchi, 2009). Types of BIC include an infant reaching for a bottle, a host holding a door open for a guest, or a driver slowing down in sight of a pedestrian. All of these actions have practical application, yet each eliminates the explicit form of communication. The purposeful performing of these actions by the communicator, allows the observer to implicitly understand the explicit message governing the actions such as “I am hungry”, “come in”, or gesturing the pedestrian to cross the street. The omission of the phrase and the gesture demonstrates how BIC can be used to replace both verbal and non-verbal forms of explicit communication.

As mentioned previously, Wood (1976) claimed that humans learn to communicate through action as children. In fact, Tronick (1989) supported Wood by saying that humans first learn to communicate through action, and added that they are even more comfortable doing so. Adults maintain the action language learned as children (reaching, looking, or holding) as a way to communicate implicitly. These additional modalities provide more robust communication when incorporated with verbal communication rather than being replaced by (explicit) verbal communication. Warfighters use BIC techniques such as tapping a radio to signal a communication issue, or loading a weapon, in sight of teammates, to signal danger is near. This supports Mehrabian and Ferris (1967) who claimed that implicit visual cues have more impact than auditory implicit communication. Castelfranchi (2009) suggested that teammates interacting in a proximate location would incorporate BIC into their collaboration and develop it as they become more experienced in their interaction.

Coordinated Management of Meaning Theory

The coordinated management of meaning (CMM) theory (Pearce & Cronen, 1980; Miller, 2002; Wood, 2000) is a rule-based theory developed in the 1970s by Pearce and Cronen. The theory is based on the notion that communication is created, coordinated, and managed based on experience. The theory emphasizes that cultural norms are used to coordinate meaning between communicators and that those norms are learned behavior patterns developed over time (Wood, 2000, p. 147). The model has six levels of coordinated communication (Table 1 on page 16) and each level focuses on different aspects of communication. CMM, although developed for mass communication, can be beneficial to HRI communication models.

Table 1: Coordinated Management of Meaning Theory (adapted from Miller, 2002)

Level	**Coordinated Meaning**
Content	Communication based on content meaning
Speech Action	Communication based on the action of the message
Episode	Communication based on the situation at hand
Relationship	Communication based on the relationship
Life Script	Communication based on self-perception, experiences, feelings and/or emotions
Cultural Pattern	Communication based on the shared system of meaning developed by a social group or society

While utilizing the cultural pattern as the foundational level, the remaining five levels can be mapped to certain aspects of cultural based HRC research. For example, each of Wood’s (2000) levels of communication meaning, content and relationship, are closely related to the five levels of the CMM model. Content meaning, sending messages the correct way, is the focus of the content and speech action level. The content level involves the proper formulation of the message, and speech action involves formulating the proper action to coincide with the message. The episode, relationship, and life script levels are related to Wood’s relationship meaning, which involves sending the correct message based on the current situation, sender/receiver relationship, or emotional state of the communicator. HRI communication research should be evaluated at each of the cultural norms levels in order to foster natural and effective communication.

Table 2 shows the research focus for all levels. For the speech action level, action language is the research focus. Action language, as explained by Montagu and Matson (1979), focuses on movements that are not used as explicit signals. They continued on to say that actions such as walking, jogging, staring, or sleeping have dual functions of 1) serving the personal need of the one performing the action, and 2) they communicate statements to those who may perceive the actions.

Table 2: Revised Coordinated Management of Meaning Theory

Level	**Coordinated Meaning**	**Research Focus**
Content	Communication based on content meaning	Functional Design
Speech Action	Communication based on the action of the message	Action Language, BIC
Episode	Communication based on the situation at hand	Situation Awareness
Relationship	Communication based on the relationship	Mental Models, Team Interaction
Life Script	Communication based on self-perception, experiences, feelings and/or emotions	Self-exploration, Self-awareness, (AI)
Culture	Communication based on the shared system of meaning developed by a social group or society	Culture

Human Robot Interaction

Isaac Asimov was one of the initial influences of imagining a world in which humans and autonomous robots coexisted. Many researchers credit the literature of Asimov as the origin of HRI (Bauer, Wollherr & Buss, 2008). Goodrich and Schultz (2007) suggested that Asimov provided the initial guidelines for researchers in HRI. In Asimov's fictional book, *I, Robot*, the three laws of robotics were:

1. *A robot may not injure a human being or, through inaction, allow a human being to come to harm.*
2. *A robot must obey the orders given to it by human beings, except where such orders would conflict with the First Law.*
3. *A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.*

Since then robots have infiltrated our society and assist humans in hospitals (Eriksson, Matari & Winstein, 2005; Groom, Srinivasan, Nass, Murphy & Bethel, 2010), and even museums (Shiomi, Kanda, Ishiguro & Hagita, 2007). Numerous ways of interacting have resulted in varying ways of defining HRI. For example, Fong, Nourbakhsh & Dautenhahn (2003) defined HRI as "the study of humans and robots, and the ways they influence each other" (p. 265). Goodrich and Schultz (2007) wrote that HRI is "a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans" (p. 203). Despite the definition, the ways that robots have been "for use by" humans have changed considerably since Asimov's imagined reality. As a result, several organizations are actively pursuing robots to take on increased roles.

The US Department of Defense (DoD) is a primary pursuer of operational robot technology (Barber, Davis, Kemper, Smith & Nicholson, 2007; Future Combat Systems, 2011;

McLurkin, 1996; Wilson, 2006;). In fact, Congress has mandated that one-third of military ground vehicles be unmanned by 2015-2020 (Chacksfield, 2008; National Defense, 2007; Taylor, 2008; Warren, 2006). Ground robots are typically used to maneuver on different terrains, and locate and deactivate mines (Kowalczuk & Czubenko, 2010). In addition to unmanned ground vehicles (UGVs), unmanned aerial vehicles (UAVs) are also taking on increased roles in military operations. In 2005, only 5% of military aircraft were unmanned, but in 2012 that number jumped to 70% (Ackerman & Shachtman, 2012). The Future Combat System (FCS) plans to employ networks of unmanned systems with varying levels of lethality and functionality, with each requiring unique rules of interacting (FCS, 2011). The plans to incorporate robots in military capacities would not be possible if robots had not made great strides in functionality since Asimov's time.

Robot Controls

Originating early in the 20th century, *teleoperation*, the operating of a system at a distance (Fong & Thorpe, 2001), gained popularity during the latter quarter of the century. Control and manipulation of these tools was similar to using a video game controller or remote-controlled toy (Sheridan, 1992). Since the most important aspect of the system was environmental maneuverability, human operators were required to closely monitor the system to ensure safety and obstacle avoidance. This type of control was, by necessity, limited to proximate interactions. EOD uses teleoperated robots to locate mines, but incorporating a dedicated operator ties a human asset to the robot asset, rather than free him/her for other duties. So just as early machine users suffered from heat and noise, collocated military operators are subject to adverse environmental conditions, thereby reducing much of the advantages of robots in military operations.

The current state of HRI research results from improvements in robot technology that occurred in the 1980s, as robots began to exhibit more behavior-based functionality (Arkin, 1998). Advances in computer technology allowed robots to make decisions based on the environment (Goodrich & Schultz, 2007). As a result, robots were able to provide force feedback, and make decisions under shared control for obstacle avoidance. Updated systems removed a portion of the burden of control from the operators, yet remained under direct control. These changes, coupled with the advent of telecommunication advances, allowed humans to control robots from remote locations. *Telepresence* (Tachi, Arai & Maeda, 1989) allowed humans to maneuver robots in extreme locations such as sea exploration (Yuh, 2000), and outer space (Fong, 2005; Fong & Nourbakhsh, 2005). Telepresence also allowed soldiers to control unmanned systems from several miles away. By incorporating shared control with telepresence, robots are able to carry out certain decisions made by the operator and provide information about environmental cues of which the operator is unaware. The military uses UAVs such as the Predator, which remove the pilot from the cockpit and allow remotely controlled robots to execute identical missions as manned entities. Humans are now removed from danger and can fly planes from remote safe zones or even half way across the globe. Although telepresence removes humans from the environment, they still remain tied to controlling the system.

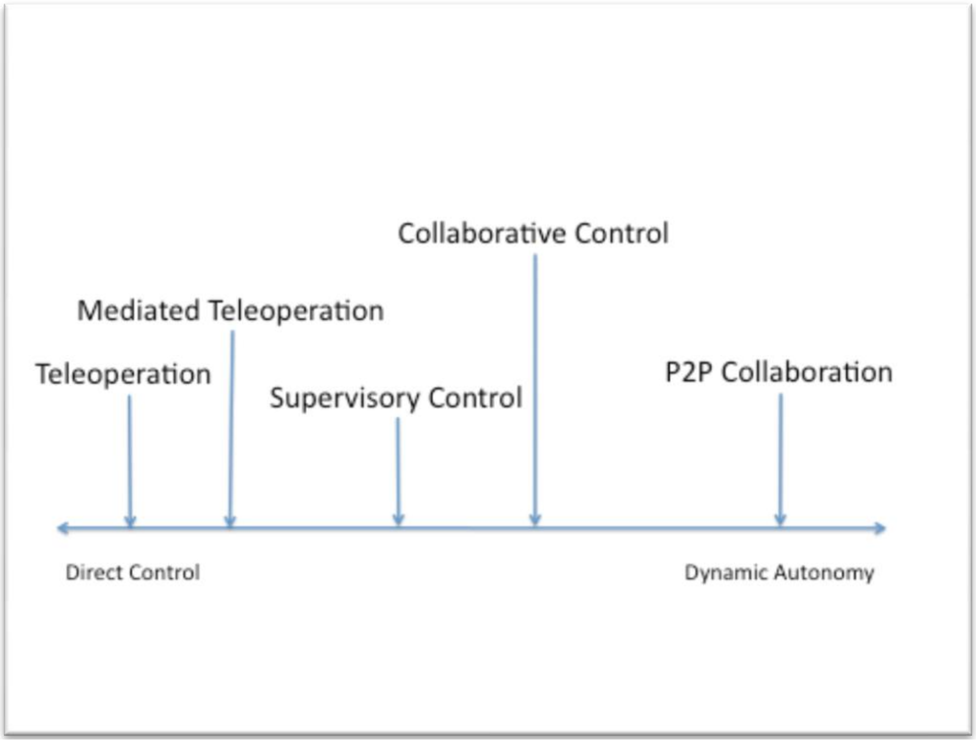

Figure 4: HRI Levels of Autonomy (adapted from Trafton et al., 2006)

This increase in proactivity shifted a portion of the operator's role to that of a supervisor (Figure 4). In fact, *supervisory control*, monitoring displays for scheduled or unscheduled events, (Wickens & Hollands, 2000) removes much of the burden of actively controlling the robot. In addition, a robot's ability to perform certain actions in a more effective and safe manner than humans led to the increase in the number of platforms being used. More robot independence required less control-based interaction (Yanco & Drury, 2002), resulting in varying changes to the nature of human and robot *interactions.* As a result, HRI began to incorporate research from various fields such as robotics, computer science, psychology, and engineering as the role of the operator changed based on the nature of control or role of the robot. Therefore, HRI expands HR relationships beyond mere tool manipulation by allowing for evaluations of increased autonomy and its affect on those relationships (Scholtz, 2003).

Previous types of controls are beneficial, but limit the robot to being used as a tool relegated to task-specific functions. The control of the robot also makes the operator susceptible to loss in awareness and skill (Mitchell, Cummings & Sheridan, 2004; Sheridan, 1997). The types of interactions that humans have with robots depend on the level and behavior of autonomy, nature of information exchange, and team structure (Goodrich & Schultz, 2007). As autonomy level increases (Figure 4), the robot transitions from a tool to a peer (Breazeal, 2004; Scholtz, 2003). Scholtz (2003) discussed the need to shift interaction with a robot from a controlled entity to a teammate. The author went on to define a teammate as humans and robots working alongside one another to accomplish specific goals, while each performs their individually assigned tasks. The NASA Robonaut program is dedicated to building an autonomous humanoid robot to work side-by-side with astronauts (Murphy, 2004). Ultimately, the DoD desires a fully autonomous operational soldier robot by 2035 (National Defense, 2007; Warren, 2006). Robots will need to transition to the right side of the autonomy spectrum shown in Figure 4 in order for the visions of NASA and the DoD to take form.

Autonomy

Automation is the performing of a task, formerly assigned to a human, by a computerized system (Parasuraman & Riley, 1997). Though rooted in machine systems, and further developed in computerized systems, automation is autonomy’s predecessor. *Autonomy* is “a robot’s ability to accommodate variations in its environment” (Thrun, 2004, p. 14). Automation and autonomy allow humans to be freed from certain tasks by shifting responsibility to the automated entity. Manual control requires the human to make and execute all decisions (Endsley & Kaber, 1999). An autonomous robot's greatest benefit would be a reduction in human workload. Advances to teleoperated systems enhanced the design of controls and visual layouts, but were unable to free the robot from control, or lighten the operator's cognitive duties. Autonomy makes it possible for human operators to use their cognitive skills more appropriately, and allows humans to oversee a plethora of tasks they would not be able to perform otherwise. However, there are certain issues that change the nature of work for the human at each level of autonomy. Consequently, Endsley & Kaber (1999) developed ten Levels of Automation (LOAs), which provide an understanding of how tasks change based on the level of automation (Table 3 on page 24). These automation levels parallel autonomy in robots.

Autonomy Progression

Teleoperation and telepresence controls remain near the *direct control* end of the spectrum of autonomy levels (Figure 4). But for tasks requiring true peer-to-peer (P2P) interaction, moving toward the right end of the spectrum is critical. Many telepresence systems incorporate shared control, thereby removing much of the burden of manual operation, and shifting a portion of decision making to the robot. But shared control requires the human to remain mentally engaged in monitoring displays and maneuvering controls, thereby creating an additional task along with manipulation.

Table 3: Levels of Automation (adapted from Endsley & Kaber, 1999)

Level	**Title**
1	Manual Control
2	Action Support
3	Batch Processing
4	Shared Control
5	Decision Support
6	Blended Decision Making
7	Rigid System
8	Automated Decision Making
9	Supervisory Control
10	Full Autonomy

Mixed-initiative interaction (MII) is a type of autonomous interaction in which interactants autonomously initiate actions or respond to another's actions appropriately (Adams et al., 2004; Driewer, Sauer & Klaus, 2007; Rosenthal & Veloso, 2010). MII is more advanced than shared control, but falls short of the supervisory control level. MII allows the robot to initiate decision generation and selection, and aids in keeping the human in the loop by allowing the robot to proactively communicate with the operator, rather than remain passively controlled or pinged. MII has proven beneficial for teleoperated and telepresence systems with long lag times such as space rovers (Fong & Thorpe, 2001). MII also benefits team performance by allowing collaboration to be based on the context of communication rather than scripted responses (Huntsberger, 2011), which allows the human to remain aware of system behavior. However, systems using MII continually keep the robot's role reduced to that of task executer, rather than an independent decision maker.

Higher degrees of supervisory control are successful in freeing the human from direct control. At the supervisory control level, the system generates and selects options while the human observes. Increased responsibility by the robot changes the operator's role from a controller to a monitor of robot actions. Since the operator shifts to becoming a passive monitor of systems, this level of enhanced autonomy results in a loss of operator system awareness and operator skill. In fact, humans tend to be less aware of system and environmental changes when a system makes a change of which the human is unaware (Endsley & Strauch, 1997).

As robots function in roles that are less tool-based and more relational-based, the need for autonomy increases (Breazeal, 2004). At the full autonomy level (Table 3), the system carries out all tasks while the human is busy executing his/her own assigned tasks. Autonomy level determines whether or not a robot is a true teammate (Groom et al., 2010), and teammates operate differently than supervisors and subordinates (Goodrich, Olsen, Crandall & Palmer, 2001). Reduced operator control increases the use and functionality of the robot—making it a greater asset to its human counterparts (Luck, McDermott, Allender & Russell, 2006).

Automation can fundamentally change the nature of cognitive demands and responsibilities (Parasuraman, 2000). Robot autonomy levels should have immediate benefit to human workload. By removing the need for prompts, cognitive demand can be reduced for operators and teammates (Johnson, Saboe, Prewett, Coovert & Elliot, 2009). But as discussed previously, increasing levels of autonomy provide a new set of experiences for the human. As joysticks and control panels are removed, humans will gravitate toward more natural ways of interacting with robots. As robots begin to interact with humans as peers, the way those changes will affect the human is unclear. Luck and his associates (2006) evaluated levels of robot autonomy and determined robot autonomy has an inverse relationship with human cognitive demand in that higher robot autonomy lowers robot error and reduces cognitive load of the operator. However, autonomy does not eliminate cognitive demand, it only redistributes it.

Workload

Although mental workload lacks a universally accepted definition, Sarno & Wickens (1995) defined it as the relationship between supply and demand of mental resources. Others defining workload discussed the relationship between information processing, mental effort and cognitive resources (Eggemeier, Wilson, Kramer & Damos, 1991; Gopher & Donchin, 1986; Hockey, 1997; Moray, 1979). Workload is affected by the demand of mental resources brought on as a result of task load and type, and when demand based on load and type compete for, or tax the supply of resources, performance suffers (Dixon & Wickens, 2003).

Workload has a very close relationship with system autonomy. Autonomy is dedicated to reducing the cognitive responsibilities of the operator by assigning tasks to the automated agent (Prewett, Johnson, Saboe, Elliott & Coovert, 2010). The level of autonomy has varying affects on mental workload. The primary relationship between autonomy and workload is that taskings change with the operator’s role, and autonomation does not necessarily translate into reduced workload. Teleoperation taxes manual control and visual resources, but increases in autonomy make demands on attention and mental processing. As tasks change from active to passive, problems arise with situation awareness and although human tasks are minimized, the operator’s workload can increase due to more tasks he has to monitor. Failure to properly collaborate with autonomous systems causes errors even more detrimental than if the operator was without the system.

Current theories of workload evolved from Kahneman's (1973) unitary resource theory. Kahneman theorized that all workload demands tax a single supply of cognitive resources. And that difficult tasks, rather than types of tasks, create a greater demand on those resources (Kahneman, 1973). Later Wickens (1976) developed the multiple resource theory (MRT). The MRT expands on the unitary model by suggesting that tasks pull from resources based on type. For example, auditory and visual tasks can be performed simultaneously by pulling from auditory and visual resources respectively, whereas the unitary model suggests that performance sufferes with concurrent tasks (Wickens, 2008). The Wickens model (Figure 5 on page 28) suggests that there are four dimensions of cognitive processing: work process, perceptual modalities, vusual channels, and processing codes.

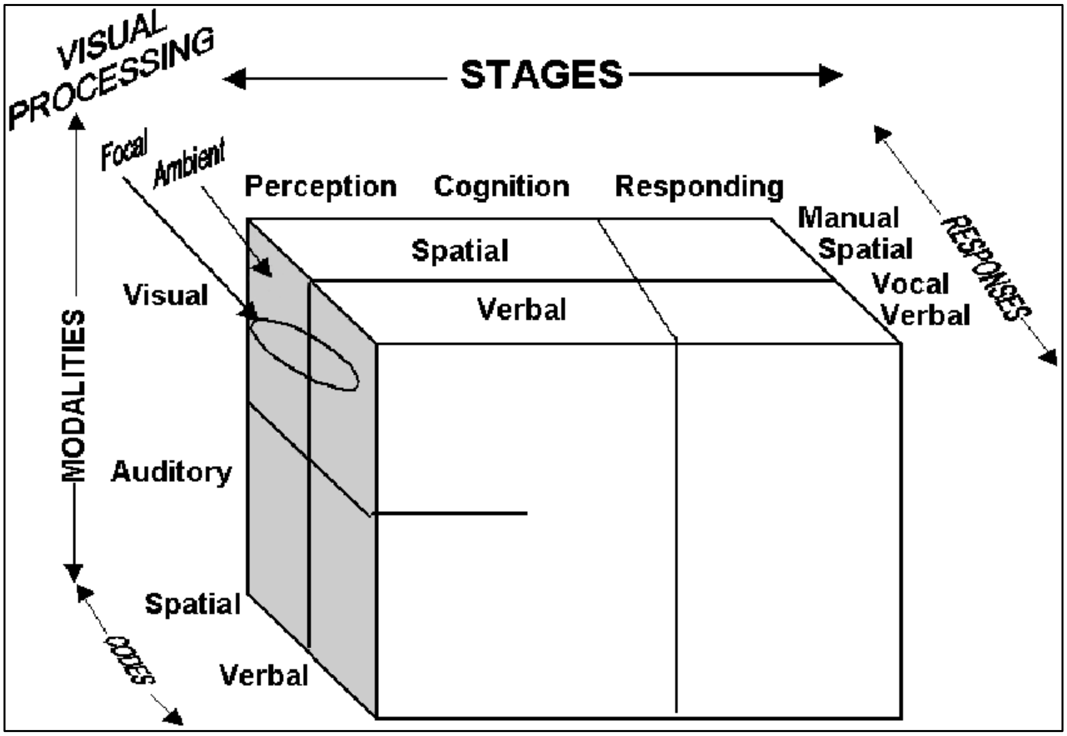

Figure 5: The 4-D MRT from Wickens (2008)

The *work process* demension divides tasks based on *perception* and *cognition*, which Wickens (2002) believed would draw from the same resource pool, from those based on *responding* to tasks, which draw from separate resources. *Perceptual modalities*, which are nested in the perception stage of the work process, divide stimuli based on the sensory modality used, such as auditory or visual. *Visual channels* are divided between focal vision, which is used to read text or recognize objects, and ambient vision, which is used for movement and self orientation. Finally, the *processing codes* dimension breaks tasks down into either spatial/manual skills or verbal comprehension/processing.

Workload can be measured using subjective questionnaires and objective physiological measures. The NASA-Task Load Index (NASA-TLX; Hart & Staveland, 1988) measures subjective workload using six subscales: Mental Demand, Temporal Demand, Performance, Effort, and Frustration. The NASA-TLX also produces a weighted average of the six subscales. The NASA-TLX has been shown to correlate to changes in workload (Matthews, Campbell, Falconer, Joyner, Huggins, Gilliland, Grier & Warm, 2002), and a high sensitivity to small workload changes (Collet, Averty & Dittmar, 2009).

EEG has been used to measure workload. Studies have shown that changes in Alpha, Beta, and Theta activity reflect changes in participant workload (Brookings, Wilson & Swain, 1996; Murata, 2005; Smith et al., 2001). Evaluating brain activity at each lobe (Taylor, Reinerman-Jones, Consenzo & Nicholson, 2010) and at each hemisphere (Dussault, Jouanin, Philippe & Guezennec, 2005) has also shown correlations to changes in workload. Indices have been derived to evaluate various aspects of workload such as the engagement index (Pope, Bogart & Bartolome, 1995; Scerbo, 2003), which uses Alpha, Beta, and Theta [$\beta/(\alpha + \theta)$]. The index of cognitive activity (ICA; Marshall, 2002) is a psychophysiological measurement of cognitive workload derived from changes in pupil dilation (Marshall, Pleydell-Pearce & Dickson, 2002). Eye tracking devices are used to measure ICA, which has been shown to reveal increases in mental workload (Marshall, 2002).

Government agencies are actively pursuing methods by which to lessen the cognitive workload for warfighters, and simultaneously limit the affects induced by new systems (Allender, 2010; Consezo, Parasuraman & De Visser, 2010; Gillian, Riley & McDermott, 2010). Currently, pilots are required to monitor or operate several UAVs simultaneously, and even share those assets with other operators. Maintaining situation awareness affects workload. By removing the need for prompts and other forms of interactions, workload can be reduced for operators and teammates (Johnson et al., 2009).

If robot autonomy is designed to decrease the cognitive load of interactants, then those benefits will be counterproductive if humans are redirecting resources to interpret robot behavior. Warfighters operate under high stress environments and any added stress, or increased workload, could prove detrimental. In order to ultimately achieve HR teams in which the robot is fully autonomous and the operator's workload is minimized, communication needs to be as natural as possible. As robots begin to take on more P2P roles, the ways in which they communicate will change (Yanco & Drury, 2002). P2P interactions will require teams to rely more on implicit communication and less on the explicit form. An important issue in P2P interactions is immediate, multi-modal feedback. Workload has been evaluated under different communication modalities and results show multimodal communication is most effective in high workload situations (Coovert, 2008). Human-human feedback occurs via communication, and humans are experts at interpreting the actions of other humans. Evaluating the current way in which humans communicate will be of great importance to communication in future HR teams. However, one drawback is the lack of theory associated with HRI and more specifically, HRI communication. A solid theoretical foundation should guide and benefit future HRI communication development.

Purpose for Present Study

Social signaling, which incorporates gestures, postures, and/or proxemics into communication, is a vital aspect of creating natural human-robot interplays. However, the explicit or implicit use of such signaling creates a dichotomy based on the intent of the signals.

Explicit communication, verbal or non-verbal, is intentional, whereas implicit communication is unintentional (Lackey et al., 2011). Research has primarily focused on the explicit nature and function of social signaling. In explicit communication, the message is primary and the action (gesture, posture, etc.) is supplementary. Since research shows that over half of human-human communication can be considered non-intentional (Mehrabian & Friar, 1969), this is an area that should not be overlooked by roboticists and researchers alike.

This study will systematically and empirically compare perceptions of humans and robots executing identical actions. This study will contribute by empirically examining the perceived implicit meaning of actions executed by robots. Work has been done to have a robot explain its actions (Brooks, 2007); however this is not optimal for situations in which humans already have high cognitive responsibilities. This study will use previous research as a foundation (Blythe, Todd & Miller, 1999; Ellis, Sims, Chin, Pepe, Owens, Dolezal, Shumaker & Finkelstein, 2005; Riek, Rabinowitch, Bremner, Pipe, Fraser & Robinson, 2010; Saerbeck & Bartneck, 2010), but develop it further by analyzing human perceptions of the intent associated with the behavior rather than the functionality of the behavior. Given that humans have strong expectations for how particular non-verbal cues reflect specific mental states of another, it is important that the robot's implicit non-verbal cues and the internal states to which they map adhere to human expectations (Breazeal et al., 2005).

This study also provides benefit to future military operations that incorporate autonomous robots into HR warfighting teams. Pereira, Pimentel, Chaimowicz & Campos (2002) found that robots communicating implicitly with limited communication capabilities performed similarly to robotic teams communicating explicitly with advanced communication systems. They also found that implicit behavior aids to provide a cover of stealth to communication, since implicit channels need not be utilized. Finally, Piunti, Castelfranchi & Falcone (2007) discovered an additional benefit to warfighters and argued that implicit communication strategies reduce the need for communication devices, which reduce cost, weight, and unreliability.

The results of this study will provide new theoretical contributions to the training science community and evidence to support or contradict current theories related to human perception of robotic behavior. Additionally, the results will have generalizable implications for the use of implicit communication in HR teams. The following chapter will detail the experiment conducted in the present study.

Research has been conducted in the area of HRI in order to include an implicit layer of communication within HRI. The majority of existing work has placed an emphasis on aiding the robot to accurately assess implicit signals sent from humans. Most of these efforts hope to aid robots in becoming better assistants, or tools, to humans (Goetz, Kiesler & Powers, 2003). Research has also evaluated implicit communication within robot-robot teams. However, little work has examined implicit modalities of communication for HR teams. Effective communication between humans and robots will only benefit the team if they share a mutual assessment of implicit cues. The aim for this work is to evaluate the effectiveness of humans at recognizing implicit actions of a non-anthropomorphic robot. Specifically, the primary goal for this research is to determine whether humans assign identical meanings to implicit cues received from a robot as they do for implicit cues received from a human by evaluating the following hypotheses:

H1: Participants will have no difference in objective performance measures for both video types.

H2: Participants will have no difference in subjective performance measures for both video types.

H3: Participants will report no difference in subjective workload after viewing both video types.

H4: Participants will demonstrate no difference in physiological responses associated with increased workload while viewing both video types.

CHAPTER THREE: METHOD

Sample Population

Experimental data was collected from a total of 54 university students, who received class credit for participating, between the ages of 18-40 (age: $M = 20.0$, $SD = 2.7$). However, one outlier was removed from the data. Of the 53 remaining participants there were 26 males (age: $M = 19.6$, $SD = 2.0$) and 27 females (age: $M = 20.5$, $SD = 3.1$). Potential participants were excluded if they were pregnant, left-handed, or on medication. Participants were requested not to consume alcohol 24 hours before the study, and to abstain from caffeine two hours prior.

Experimental Task

The experimental task required participants to view video recorded scenarios of human and robot soldiers executing movements associated with standard military operations in a deployed environment. The scenarios were prerecorded using standard recording video equipment. The participant's task was completed on a standard desktop computer with a 22" (16:10 aspect ratio) monitor with a mouse. Each participant was tasked to view the executed movement, categorize each movement based on its implicit nature, and select a level of confidence in their chosen answer. Scenarios consisted of one *entity* executing each of the five *implicit communications* from two different angles. In one angle the *entity* moved from right to left, and in the other left to right. The participants saw each clip twice for a total of 20 clips per scenario.

Experimental Design

Independent Variables

The experiment was designed as a 2 x 2 x 5 repeated-measures design with three independent variables: *type*, *size*, and *implicit communication*. All 24 possible orders of the *type* x *size* condition were randomized and balanced for presentation to the participants. Since this was a repeated-measures design, each participant viewed each *entity*, as four separate scenarios, execute all five *implicit communications*. In addition, the presentation order of each *implicit communication* was randomized using a Latin Rectangle.

Figure 6: Screenshot of Human Scenario

Entity

The four conditions for *entity* were Human 1 (Figure 6), Human 2, Robot 1, and Robot 2 (Figures 7 & 8 on page 36). Human 1 was 6’1, 200 lbs, Human 2 was 5’10, 160 lbs, Robot 1 was a four-wheeled robot of size 47 x 33 x 25 in^3, and Robot 2 was a four-wheeled robot of size 12 x

13 x 7 in^3. Research assistants from the Active Lab at the Institute for Simulation and Training (IST) controlled the robots via teleoperation while recording the videos.

Figure 7: Screenshot of Robot 1 Scenario

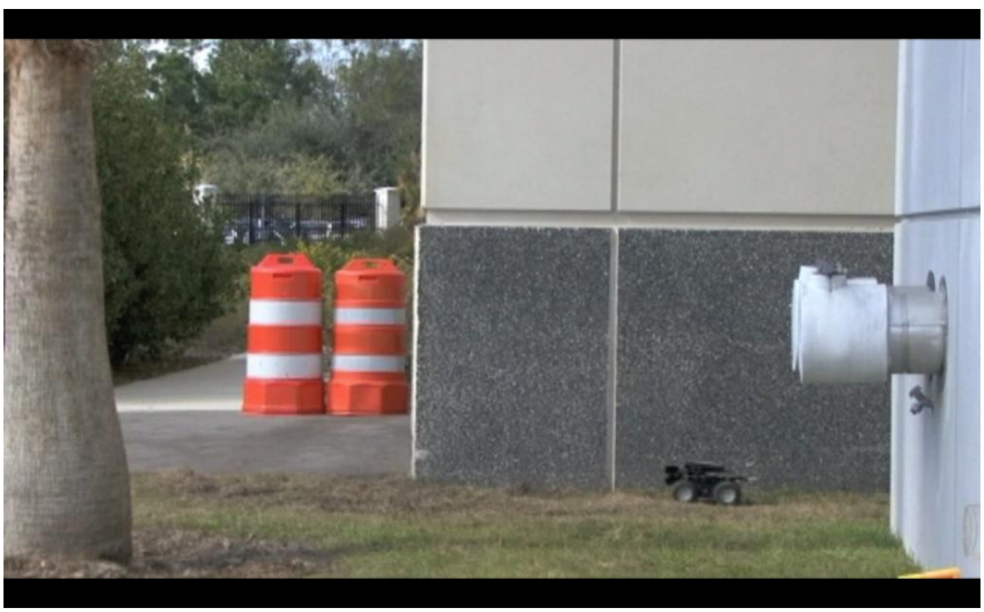

Figure 8: Screenshot of Robot 2 Scenario

Implicit Communication

The Headquarters Department of the Army's Manual of Common Tasks: Warrior Skills Level 1 (HDAMCT; 2009) manual consists of several tasks that a soldier is required to carry out during combat. The manual is over 600 pages long and provides an extensive list of duties expected of a soldier. Duties include supporting an injured soldier, reacting to signals, and engaging the enemy. A few selected duties are shown in Table 4 and correlate to action languages (fleeing, hiding, pursuing, investigating, and patrolling) that coincide with activities that a robot soldier should be able to perform. These duties have been chosen for this experiment.

Table 4: Implicit Communication Actions

Action Language	**Definition**	**Compiled Common Tasks**
Fleeing	Run away from danger	React to attack, gunfire, protect yourself
Hiding	Hide from danger	React to attack, gunfire, protect yourself from enemy
Pursuing	To chase in order to overtake	Engage an enemy
Investigating	To check, scan or evaluate	React to a flare, examine an injury, recover a mine
Patrolling	To monitor an area	Monitoring an area to check for danger

Dependent Variables

Classification

Participants were required to classify each video clip based on a list provided. The list included the following seven options: Patrolling, Hiding, Retreating, Investigating, Pursuing, I do not know, and Other. Although there is no correct answer for each video, expected answers, based on definitions from the HDAMCT, were used to evaluate participant answers.

Confidence

Each participant was required to self-report a level of confidence for his/her answer for each video clip. The confidence level was based on a seven-point Likert-type scale ranging from 1 (strongly not confident) to 7 (strongly confident).

Participant Questionnaires

Participants completed a demographics questionnaire (Appendix A) to record information such as age, gender, and experience level with certain types of technologies. A restrictions checklist (Appendix B) was used to ensure that the participant met the inclusion criteria: normal state of health, normal or corrected vision, and handedness.

Subjective Stress Measure

The Dundee Stress State Questionnaire (DSSQ; Matthews et al., 2002) was used to assess each participant's subjective stress level following each experimental scenario. Due to time limitations, the short form was used (Helton, 2004). The form allows participants to report changes in Task Engagement, Distress, and Worry. The DSSQ consists of a pre-test that was completed before beginning the experiment (Appendix C) and a post-test that was completed following each experimental scenario (Appendix D).

Subjective Workload Measure

The NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) was used to measure the participant's subjective workload from each experimental scenario. The measure produces six workload subscales: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration Level, as well as a single combined measure of Global Workload. The Global Workload measure is calculated as the weighted average of the six subscales, with each subscale weighted according to the number of times it is selected as the more important contributor in the paired comparisons section. The NASA-TLX was administered on the computer through a standard computer program (Appendix E).

Physiological Measures

Electroencephalogram (EEG)

A system from Advanced Brain Monitoring (Figure 9 on page 41) was used to monitor Electroencephalography (EEG), which is the recording of electrical brain activity along the scalp (Gevins & Smith, 2007). The system uses the B-Alert X10 that samples at 256 Hz (256 samples per second). The ten-channel system has a nine-channel (F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4) EEG cap, with two references at each mastoid, and 2 electrocardiography (ECG) connectors, which monitor the activity of the heart and act as the tenth channel. Power spectral density analysis is used to compute values for Alpha (8-13 Hz), Beta (14-26 Hz), and Theta (4-7 Hz) activity at each site (Taylor et al., 2010).

EEG was used to assess the workload of the participants. Studies have shown that changes in Alpha, Beta, and Theta activity reflect changes in participant workload (Brookings et al., 1996; Murata, 2005; Smith et al., 2001). Evaluating brain activity at each lobe (Taylor et al., 2010) and at each hemisphere (Dussault et al., 2005) has also shown correlations to changes in workload. The engagement index (Pope, Bogart & Bartolome, 1995; Scerbo, 2003) was derived to evaluate workload by using a single value consisting of a relationship between Alpha, Beta, and Theta [$\beta/(\alpha + \theta)$]. Data from sensor sites Cz, Pz, P3, and P4 was used, with each individual's baseline value subtracted from their activity during the scenario to produce a change from baseline value. In addition, ECG records information concerning participants' heart rate, heart-rate variability, and inter-beat interval, which have been shown to reveal increases in workload (Veltman & Gaillard, 2010).

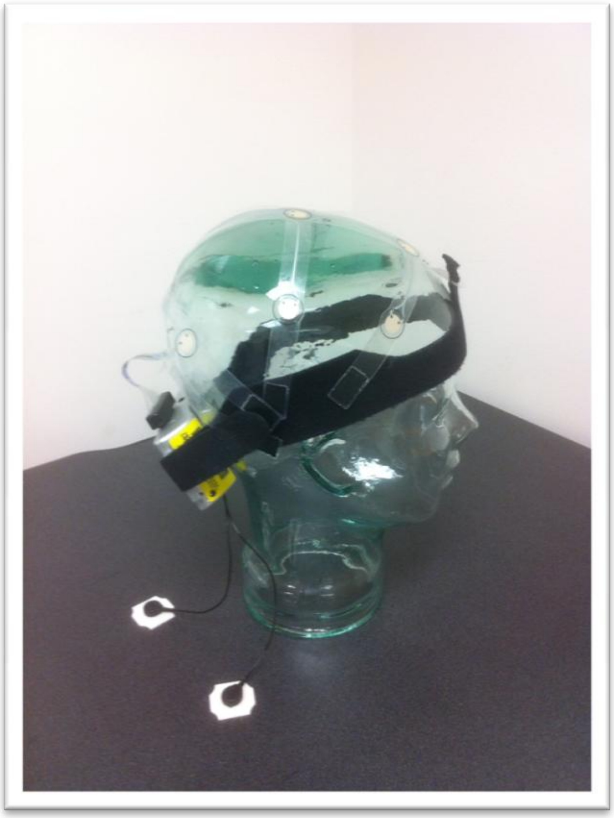

Figure 9: Advanced Brain Monitoring Ten Channel EEG System

Eye Tracking

The faceLAB 5 product by Seeing Machines was used to monitor *eye tracking*, aspects of the gaze and position of the eye (McCarley & Kramer, 2007). The faceLAB 5 device consists of a pair of cameras which are located off of the body (non-obtrusive) and samples at 60 Hz. The metrics recorded are Marshall's Index of Cognitive Activity (ICA; Marshall, 2002), as well as information about randomness of fixation points, fixation duration, saccade duration, head position, blink rate, and blink length. The metric used for this research will be the ICA, which tracks changes in pupil dilation and reveals increases in cognitive effort (Marshall, 2002).

Experimental Procedure

After the restrictions checklist was completed, acceptable participants were provided with an Informed Consent form that detailed their rights as a research participant, the purpose of the study, an overview of the procedure, and the potential risks associated with participating.

The EEG cap was placed on the participant. The cap was aligned using the nasion (the midpoint between the eyes, just above the bridge of the nose) and inion (the bump found at the center of the occipital bone on the back of the skull). If necessary, the participant's hair was parted at the site of each EEG sensor to ensure direct contact between the sensor and the scalp. Conductive gel was also used to ensure proper connection and to reduce the electrical impedance of the signal. In addition to the nine EEG sensors, the system used two reference electrodes – one on each mastoid bone (behind the ear), which were attached directly to the participant's skin using adhesive pads. The tenth channel, consisting of two ECG sensors, was connected to the participant's upper right collarbone and lower left rib bone. Once all sensors were in place, they were tested to confirm that the electrical resistance of each was below 40 kΩ. The participant was asked to relax with their eyes open while the data was collected. The data recorded during this period was used as a baseline to which recordings made during the experimental scenarios compared, accounting for the random variation in individual physiological differences.

Once the baseline EEG data was collected, the participant was seated in front of a computer monitor and asked to complete a validated calibration technique that was developed by the eye tracker company. First, the research assistant adjusted the eye tracker to locate the participants' face. Then a computer program automatically presented a series of calibration points that were used to map their visual field to the computer screen; the participant was guided to set their gaze on each point one at a time and in order. The research assistant asked the participant to shift their gaze to the next location only after a valid measure for that location was obtained. A valid measure was determined by the amount of data loss while viewing each calibration point.

The participant then completed the demographics questionnaire and the DSSQ pre-test. Following these questionnaires, the participant viewed the experimental rules via a PowerPoint presentation. Following the presentation, the participant completed a brief training scenario in order to become familiar with operating the system.

Following the training scenario, the participant began the first experimental scenario. The order in which all participants completed the experimental scenarios was randomized and balanced. Participants viewed the scenarios one *entity* at a time. After viewing the clips, they were tasked to assign a meaning communicated by each action, and their level of confidence in their choice using a seven-point Likert type scale. A dialogue box (Figure 10 on page 44) appeared at the end of each clip, and participants chose one of the *implicit communications*. After an option was selected, confirmed, and confidence level chosen, the next clip began.

After completing the first scenario, the participant completed the DSSQ Post-Test and the NASA-TLX. This pattern was repeated for the remaining three levels of *entity*. After the completion of the fourth experimental scenario and questionnaires, the EEG cap and sensors were removed from the participant, who was then allowed to leave.

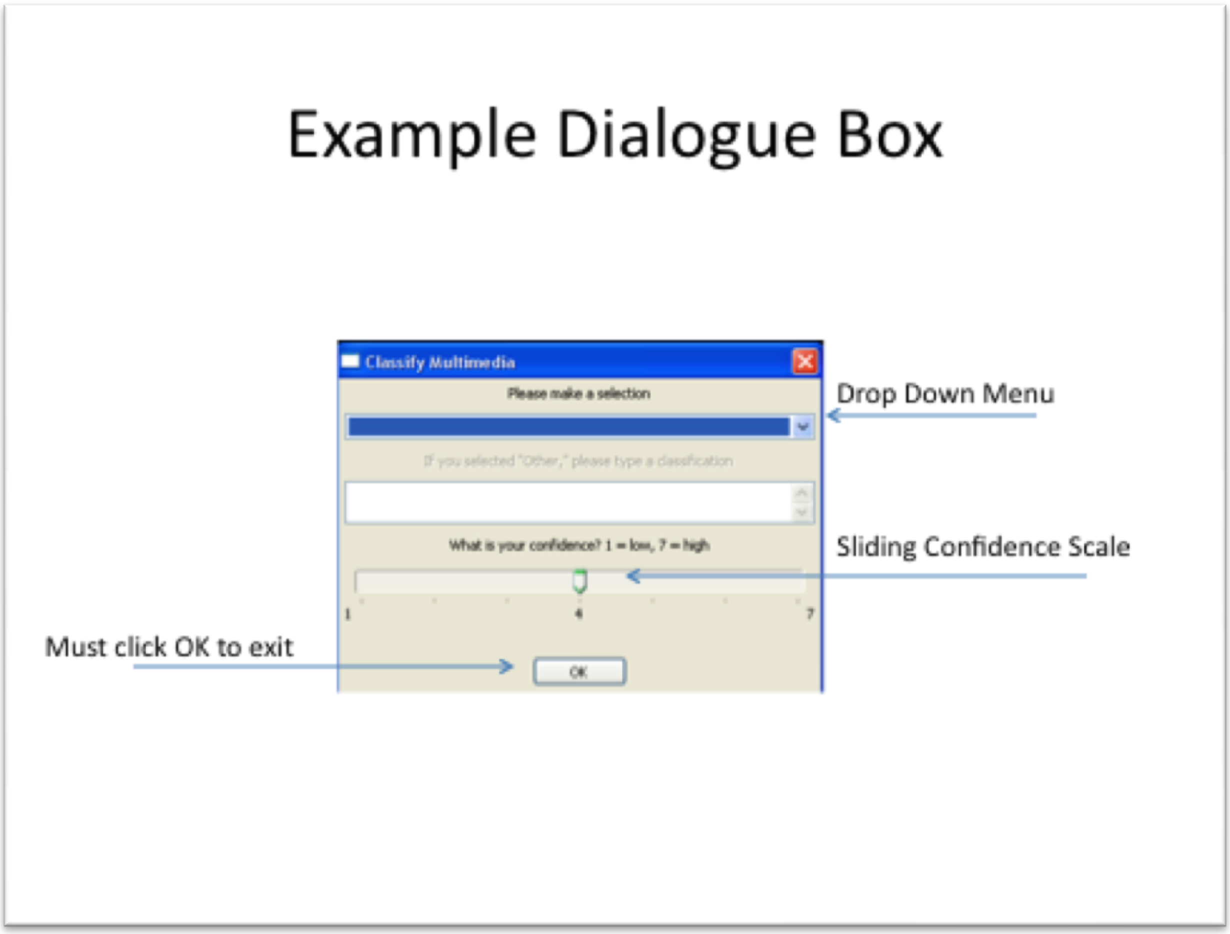

Figure 10: Screenshot of dialogue box

CHAPTER FOUR: RESULTS

Rationale

The rationale for choosing the following analysis is to examine communication saliency. Although there are no correct answers, expected answers, based on the HDAMCT (2009), were used to score each *implicit communication* video for answer correctness. This analysis is based on those results. The answer selected for each *implicit communication* matched our expected answer over 50% of the time for each *implicit communication* video. The results showed that the expected answer was also the most frequent answer choice for each *implicit communication* for each *type* and *entity*. ** Denotes that sphericity was violated and the Greenhouse-Geisser correction was used.

Order Effects

Answer Correctness

Unless stated otherwise, answer correctness, which is the measure of a match between a participant's answer and the expected answer, was evaluated using repeated-measures ANOVAs with a 2 x 2 x 5 structure with variables *type* (Human and Robot), *size* (Large and Small), and *implicit communication* (Patrolling, Hiding, Retreating, Investigating, and Pursuing). Further analysis was conducted for each *entity* (Human 1, Human 2, Robot 1, and Robot 2) as necessary.

Answer Correctness for Scenario Order

Significant main effects were found for answer correctness based on scenario order [F(2.97, 3099.61) = 10.67, $p = 0.001$]**. Participants scored significantly lower for Scenario 1 (M = 77.9%, SD = 0.42) than Scenario 2 (M = 84.2%, SD = 0.36), Scenario 3 (M = 85.1%, SD = 0.36), and Scenario 4 (M = 85.6%, SD = 0.35).

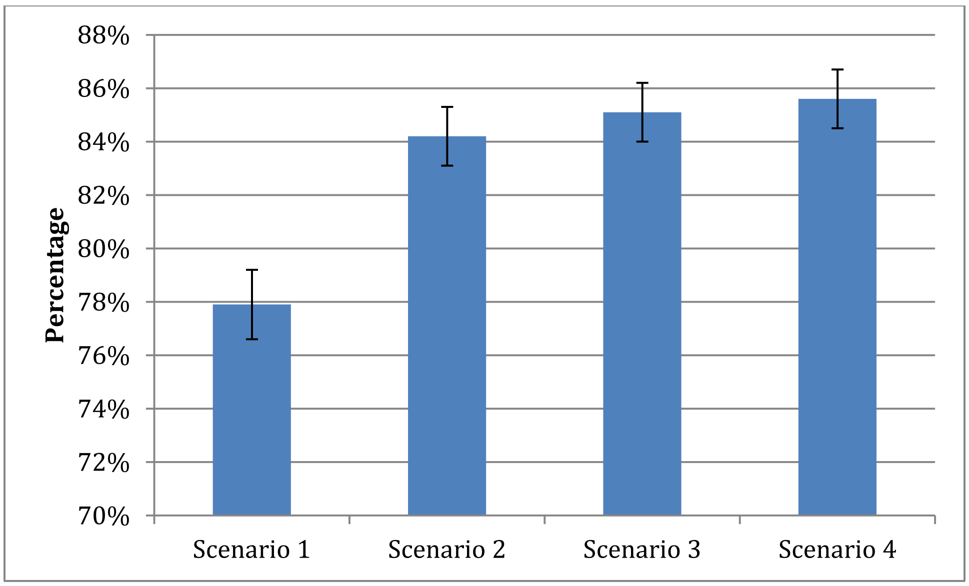

Figure 11: Mean Answer Correctness for each Scenario

Answer Correctness for Scenario Order by Type

Significant main effects were found for answer correctness based on *type* [F(1, 1058) = 7.736, $p = 0.006$] for Scenario 2. Participants scored significantly higher on Human videos (M = 87%, SD = 0.34) than Robot videos (M = 81%, SD = 0.39) during Scenario 2. There were no significant differences by *type* for Scenarios 1, 3, and 4.

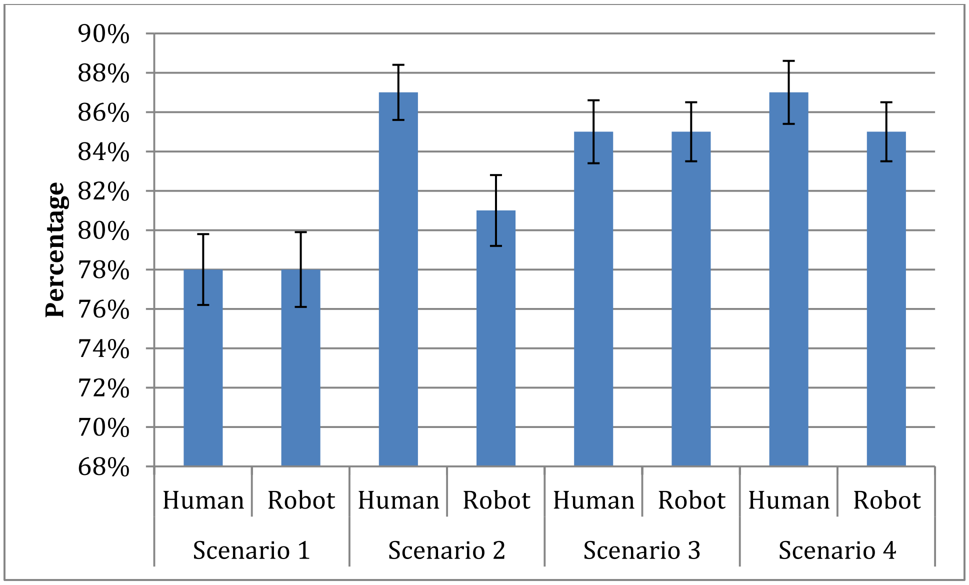

Figure 12: Mean Answer Correctness for each Scenario by Type

Answer Correctness Grouped by Entity Order

Answer correctness was evaluated using a between-subjects ANOVA to compare groups who viewed a human first to those who viewed a robot first. No significant main effects were found.

Subjective Confidence

Subjective confidence for Scenario Order

Significant main effects were found for subjective confidence based on scenario order [F(2.93, 3099.61) = 28.99, p = 0.001]**. Participants reported significantly lower confidence for Order 1 (M = 5.83, SD = 1.08) than for Order 2 (M = 6.05, SD = 1.01), Order 3 (M = 6.12, SD = 1.01), and Order 4 (M = 6.13, SD = 1.05). Subjective confidence was also significantly higher for Order 4 (M = 6.13, SD = 1.05) than for Order 2 (M = 6.05, SD = 1.01).

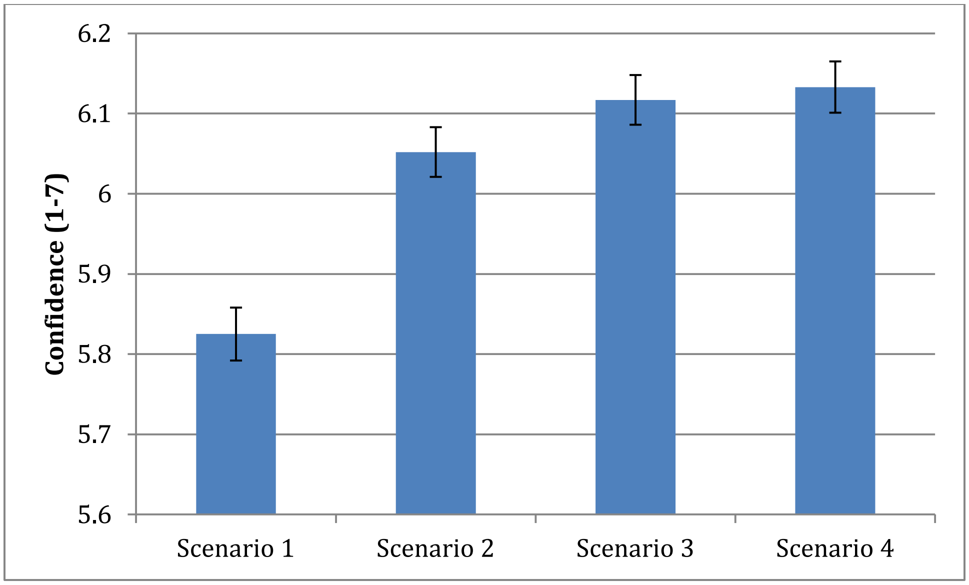

Figure 13: Mean Subjective Confidence for Scenario Order

<u>Subjective Confidence for Scenario Order by Type</u>

Significant main effects were found for subjective confidence based on *type* for each Scenario. Participants reported significantly higher confidence on Human videos than Robot videos during each Scenario. Statistical values for each Scenario are listed in Table 5 below.

Table 5: Statistical Values for Subjective Confidence by Scenario Order

Scenario	F (1, 1058) Value	P Value	Human *M*	Human *SD*	Robot *M*	Robot *SD*
1	7.47	0.006	5.91	1.02	5.73	1.14
2	14.52	0.001	6.16	0.99	5.92	1.02
3	6.69	0.010	6.2	1.04	6.04	0.99
4	19.71	0.001	6.32	0.90	5.98	1.13

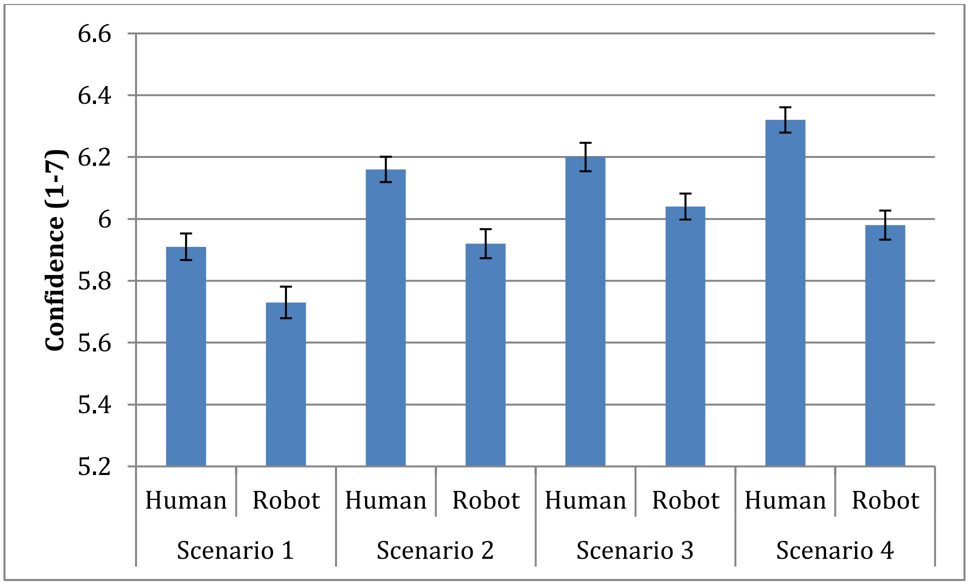

Figure 14: Mean Subjective Confidence for each Scenario by Type

<u>Subjective confidence Grouped by Entity Order</u>

Subjective confidence was evaluated using a between-subjects ANOVA to compare groups who viewed a human first to those who viewed a robot first. No significant main effects were found.

<u>Performance</u>

Answer Correctness

<u>Answer Correctness by Type & Entity</u>

Significant main effects were found for answer correctness based on *type* [F(1, 1059) = 4.26, *p* = 0.039]. Participants scored significantly higher for Human Videos (*M* = 84.1%, *SD* = 0.31) than Robot Videos (*M* = 82.3%, *SD* = 0.32).

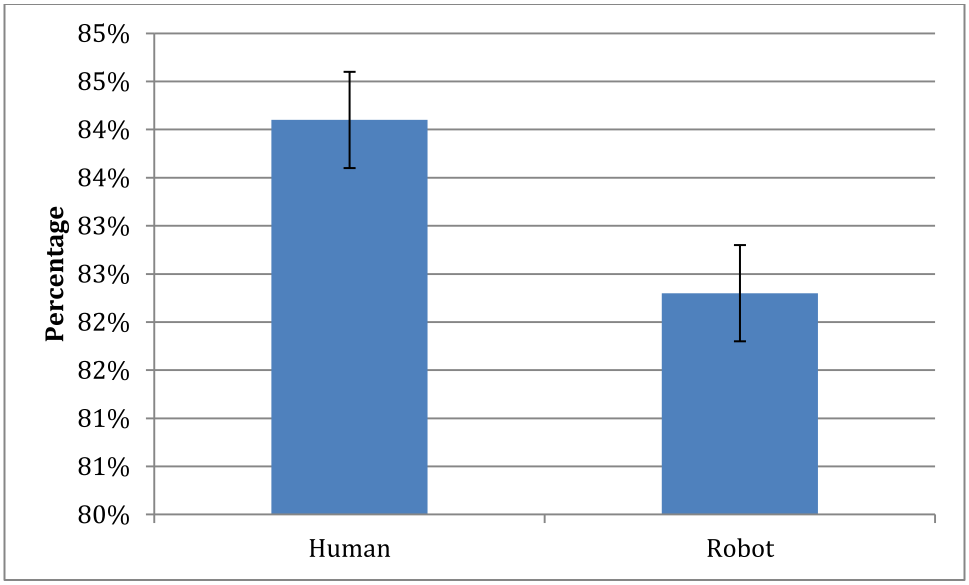

Figure 15: Mean Answer Correctness by Type

Significant main effects were found for answer correctness based on *entity* [F(3, 3177) = 5.52, p = 0.001]. Participants scored significantly higher for Human 2 (M = 85.7%, SD = 0.35) than Human 1 (M = 82.5%, SD = 0.38) and Robot 2 (M = 80.8%, SD = 0.39). Participants also scored significantly higher for Robot 1 (M = 83.8%, SD = 0.37) than Robot 2 (M = 80.8%, SD = 0.39).

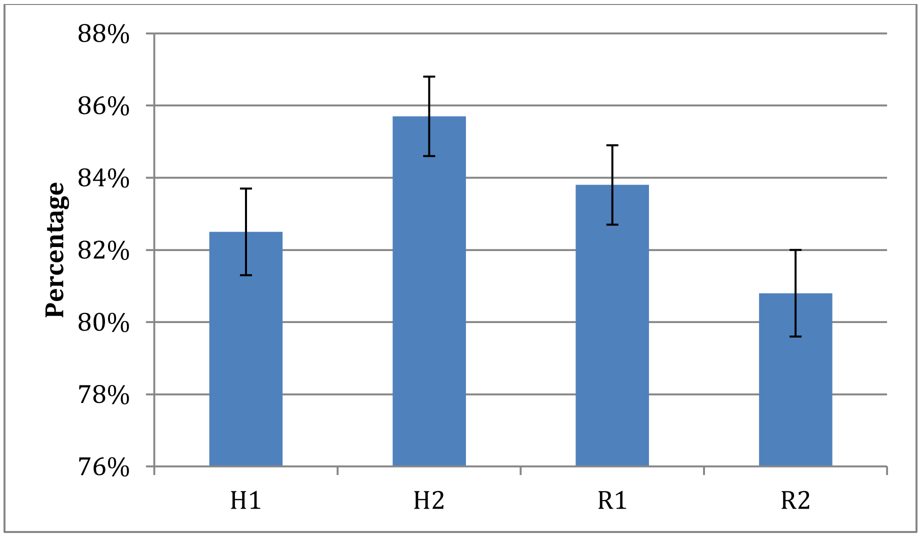

Figure 16: Mean Answer Correctness for each Entity

Answer Correctness by Type for each Implicit Communication

There were no significant main differences for *type* answer correctness for any of the implicit communications. Since answer correctness for Patrolling videos had an overall mean of 76%, and answer correctness for Investigating videos had an overall mean of 61%, Pareto charts for selected answers for both *implicit communications* are shown in Figure 16 and 17 on page 53.

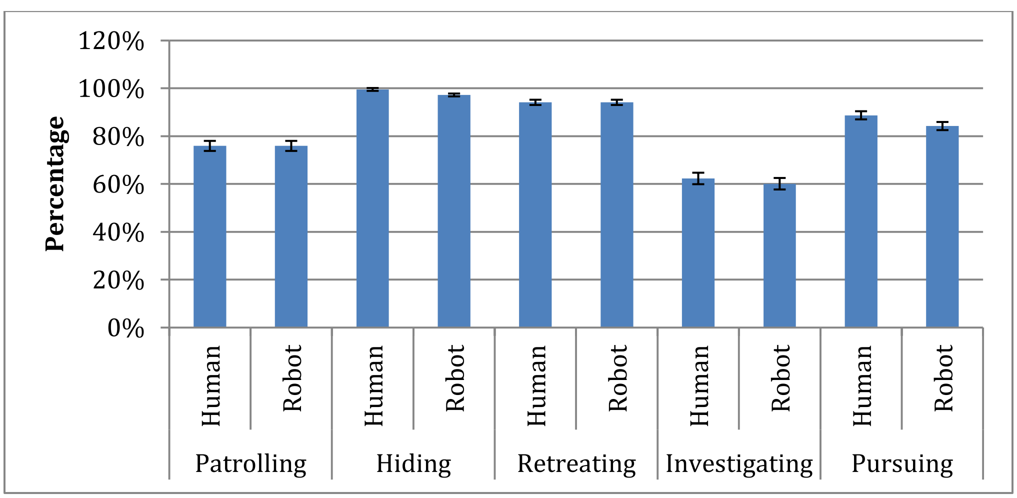

Figure 17: Mean Answer Correctness by Type for each Implicit Communication

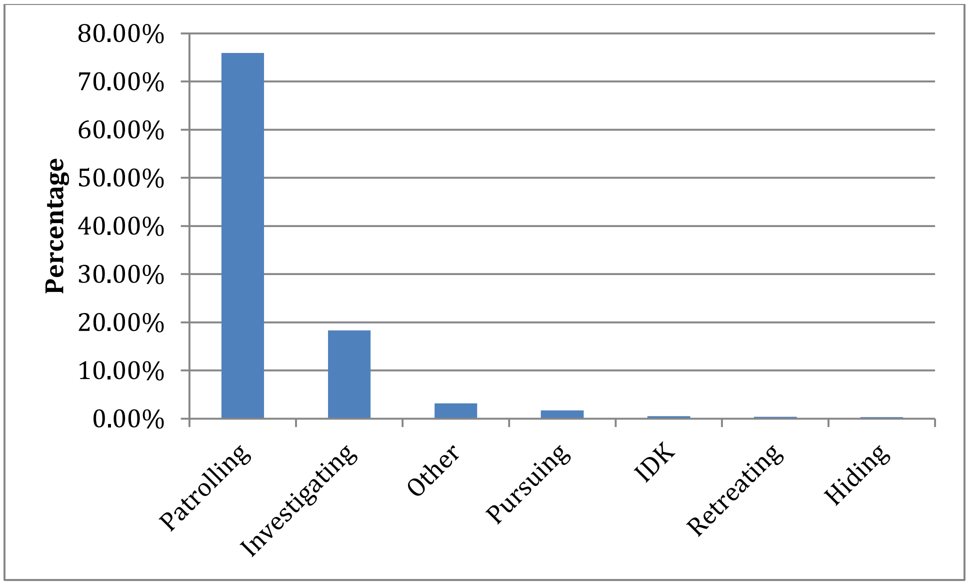

Figure 18: Selected Answers for Patrolling Videos

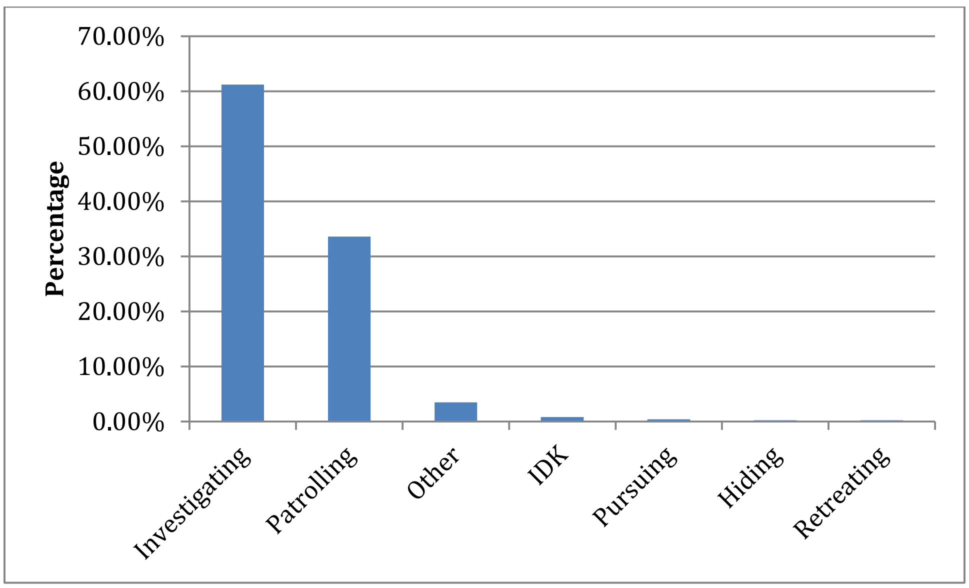

Figure 19: Selected Answers for Investigating Videos

Answer Correctness by Implicit Communication

Significant main effects were found for answer correctness based on *implicit communication* [F(3.01, 2552.29) = 169.04, *p* = 0.001]**. Participants scored significantly higher for Hiding (*M* = 98.3%, *SD* = 0.13) than Patrolling (*M* = 75.9%, *SD* = 0.43), Retreating

(*M* = 94.1%, *SD* = 0.24), Investigating (*M* = 61.2%, *SD* = 0.49), and Pursuing (*M* = 86.4%, *SD* = 0.34). Participants scored significantly higher for Retreating (*M* = 94.1%, *SD* = 0.24) than Patrolling (*M* = 75.9%, *SD* = 0.43), Investigating (*M* = 61.2%, *SD* = 0.49), and Pursuing (*M* = 86.4%, *SD* = 0.34). Participants scored significantly higher for Pursuing (*M* = 86.4%, *SD* = 0.34) than Patrolling (*M* = 75.9%, *SD* = 0.43). Investigating scores were significantly lower than all other *implicit communications*.

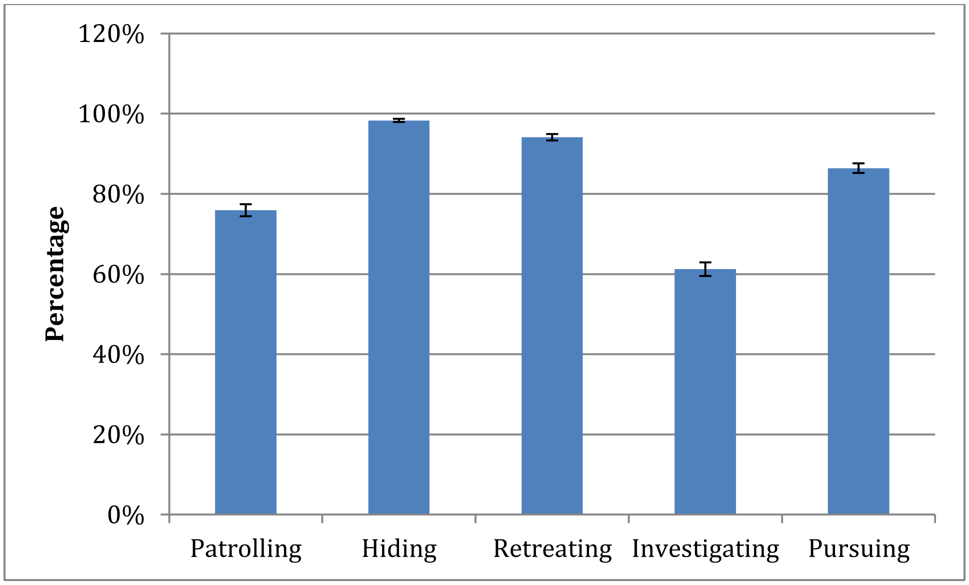

Figure 20: Mean Answer Correctness for each Implicit Communication

Subjective Confidence

Unless stated otherwise, subjective confidence was evaluated through repeated-measures ANOVAs using a 4 x 5 structure with variables *entity* (Human 1, Human 2, Robot 1, and Robot 2), and *implicit communication* (patrolling, hiding, retreating, investigating, and pursuing).

Subjective Confidence by Type

Significant main effects were found for subjective confidence based on *type* [F(1, 1059) = 80.89, $p < 0.001$]. Participants reported significantly higher confidence for Human videos (M = 6.14, SD = 0.85) than Robot videos (M = 5.92, SD = 0.93).

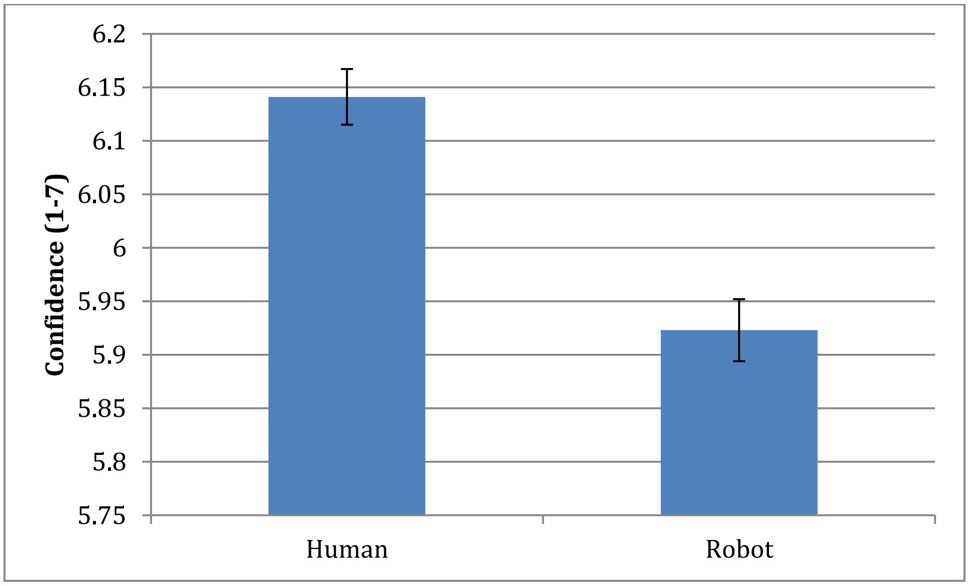

Figure 21: Mean Subjective Confidence by Type

Subjective Confidence by Entity

Significant main effects were found for subjective confidence based on *entity* [F(3, 3177) = 31.77, $p = 0.001$]. Participants reported significantly higher confidence for Human 1 (M = 6.09, SD = 1.04) and Human 2 (M = 6.19, SD = 0.95) than Robot 1 (M = 5.91, SD = 1.05) and Robot 2 (M = 5.93, SD = 1.11). Subjective confidence was also significantly higher for Human 2 (M = 6.19, SD = 0.95) than Human 1 (M = 6.09, SD = 1.04).

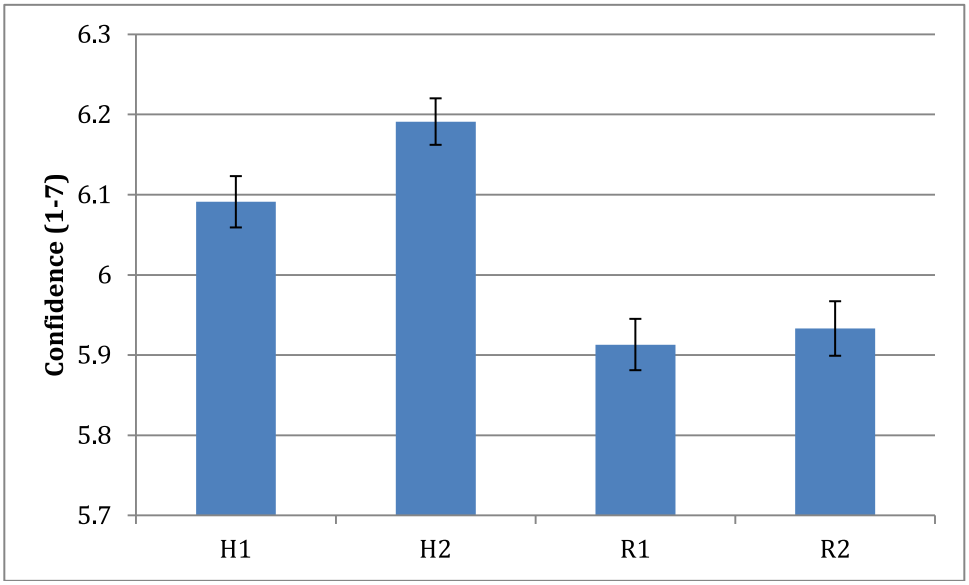

Figure 22: Mean Confidence for each Entity

Subjective Confidence by Entity for each Implicit Communication

Patrolling

Significant main effects were found for subjective confidence based on *type* for *implicit communication*. Participants reported significantly higher confidence for answers on Human videos than answers on Robot videos for each *implicit communication* except Investigating. Statistical values for each Scenario are listed in Table 6 below.

Table 6: Statistical Values for Subjective Confidence by Implicit Communication

Implicit Comm.	F(1, 846) Value	P Value	Human *M*	Human *SD*	Robot *M*	Robot *SD*
Patrolling	9.45	0.002	5.83	1.20	5.58	1.17
Hiding	13.09	0.001	6.46	0.72	6.26	0.90
Retreating	4.32	0.038	6.28	0.88	6.15	0.97
Investigating	1.51	0.220	5.97	1.00	5.89	1.07
Pursuing	32.50	0.001	6.15	1.00	5.74	1.11

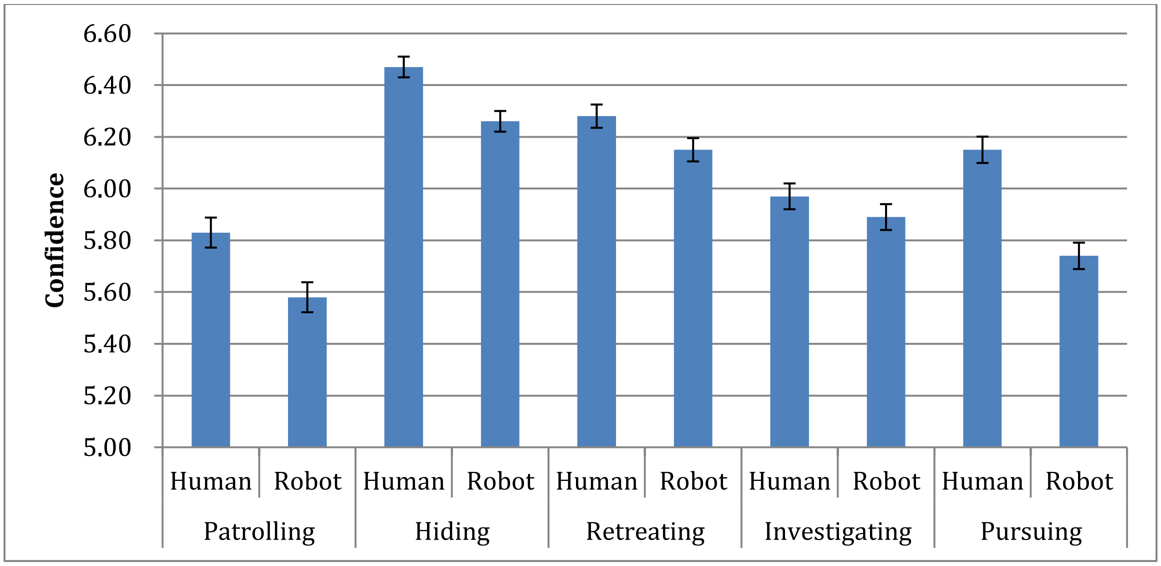

Figure 23: Mean Confidence for each Entity by Implicit Communication

Subjective Measures

Stress (DSSQ)

Responses to the DSSQ short version were used to calculate values of Distress, Engagement, and Worry. The values computed from the baseline measure administered prior to the experimental sessions were subtracted from the values obtained from each experimental scenario to account for individual variation in baseline stress. The resulting change scores were each evaluated through repeated-measures ANOVAs using a 4 x 5 structure with variables *entity* (Human 1, Human 2, Robot 1, and Robot 2), and *implicit communication* (patrolling, hiding, retreating, investigating, pursuing). There were no significant main effects for Distress, Engagement, or Worry across *type* or *entity*.

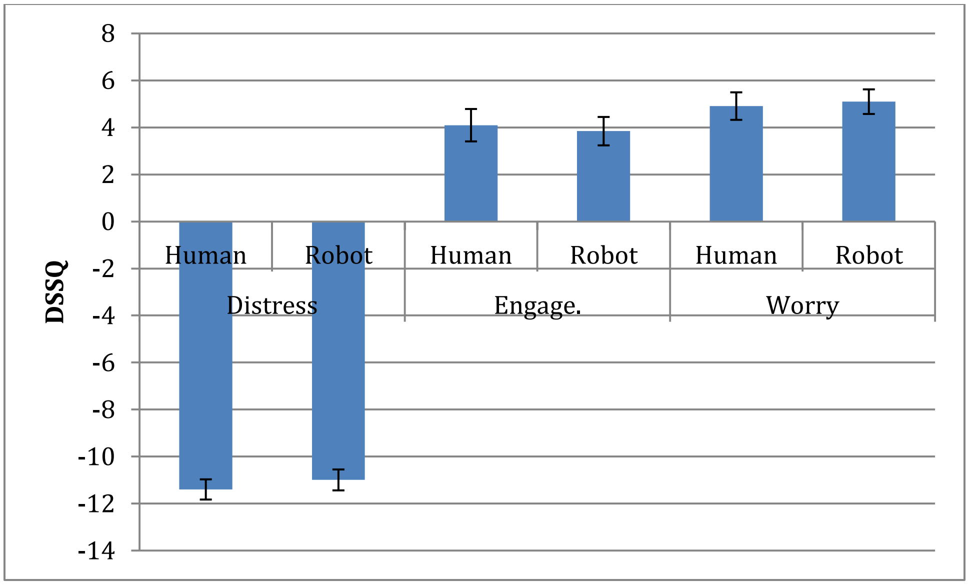

Figure 24: Mean Scores for DSSQ by Type

Workload (NASA-TLX)

The NASA-TLX produced six workload subscales: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration Level, as well as a single combined Total Workload based on the weighted average of the six subscales. Each of these values was evaluated through repeated-measures ANOVAs using a 4 x 5 structure with variables *entity* (Human 1, Human 2, Robot 1, and Robot 2), and *implicit communication* (patrolling, hiding, retreating, investigating, pursuing). There were no significant main effects across entity for Mental Demand, Physical Demand, Temporal Demand, Effort, Frustration, or Total Workload.

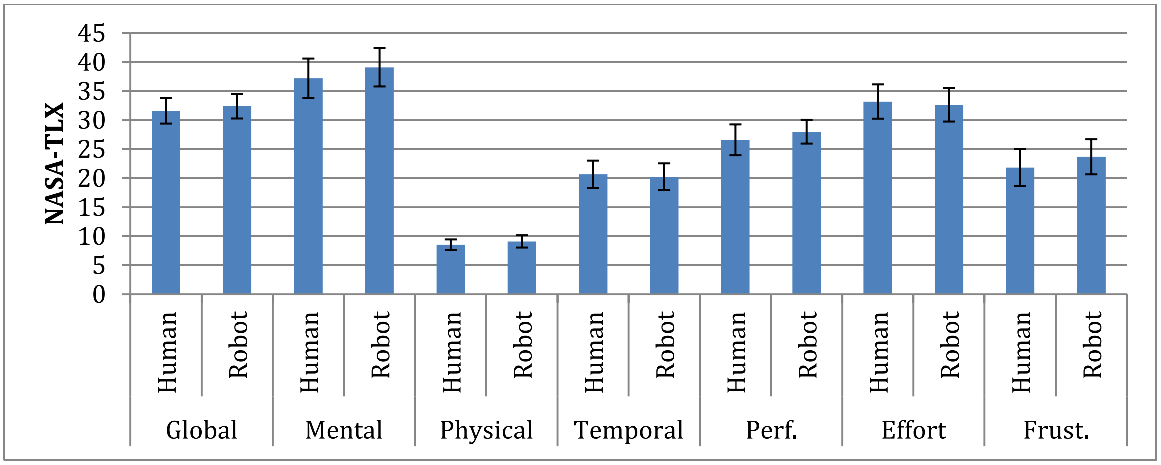

Figure 25: Mean Values for NASA-TLX Subscales for each Type

Physiological Measures

Experimental data was collected from a total of 54 university students (age: *M* = 20.0, *SD* = 2.7). However, due to errors with the physiological sensors 2 participants were removed from the data. Of the 52 remaining participants there were 25 males (age: *M* = 19.6, *SD* = 2.0) and 27 females (age: *M* = 20.5, *SD* = 3.2).

Electroencephalogram (EEG)

Results from this analysis yielded no significant main effects or interactions across *type.*

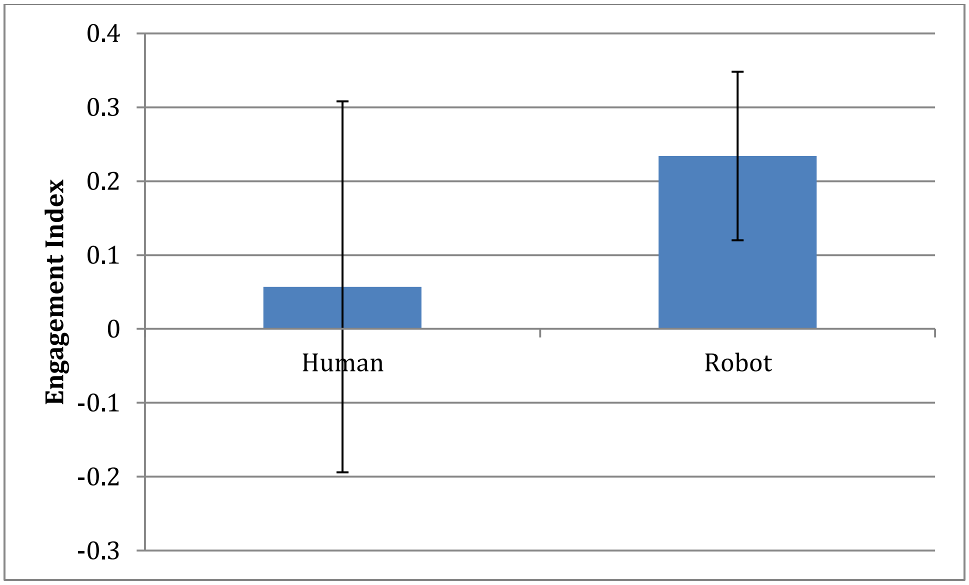

Figure 26: Mean Values for the Engagement Index by Type

Electrocardiogram (ECG)

Data collected from the ECG was used to determine heart rate variability (HRV), which is the statistical variance of the time period between heartbeats. *Type* was found to have a significant effect on HRV [F(1, 51) = 5.43, p = 0.024]. Participants had significantly higher HRV while completing Robot videos (M = 6.60, SD = 18.04) than while completing Human videos (M = 3.54, SD = 19.42).

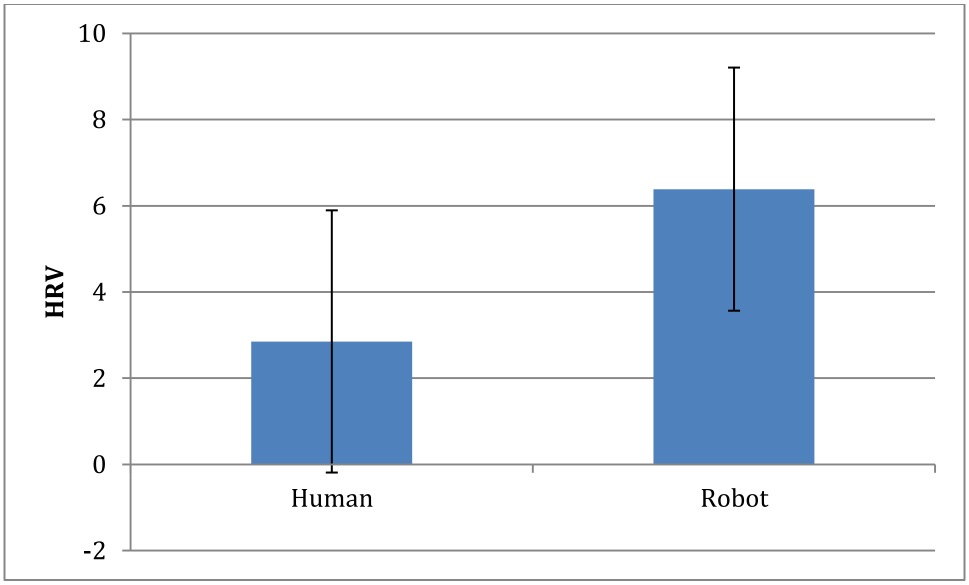

Figure 27: Mean HRV Change in Baseline by Type

Entity was found to have a significant effect on HRV [F(3, 153) = 2.83, $p = 0.040$]. Participants had significantly higher HRV while completing the Robot 1 ($M = 7.96$, $SD = 19.86$) scenario than while completing the Human 1 ($M = 2.05$, $SD = 20.14$) scenario.

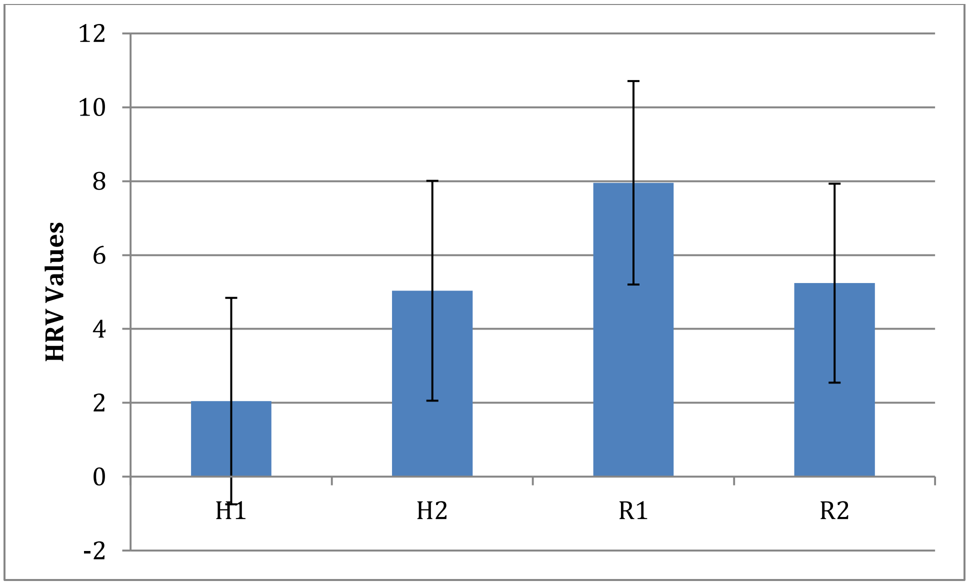

Figure 28: Mean HRV Change from Baseline for each Entity

Eye Tracker

Experimental data was collected from a total of 54 university students (age: *M* = 20.02, *SD* = 2.7). However due to errors with the eye tracker, 9 participants were removed from the data. Of the 45 remaining participants there were 24 males (age: *M* = 19.7, *SD* = 2.1) and 21 females (age: *M* = 20.5, *SD* = 3.6).

Index of Cognitive Activity

Type was found to have a significant effect on ICA [F(1,44) = 19.09 *p* < 0.001]. Participants had significantly higher ICA values while viewing robot videos (*M* = 0.33, *SD* = 0.09) than while viewing Human videos (*M* = 0.30, *SD* = 0.08).

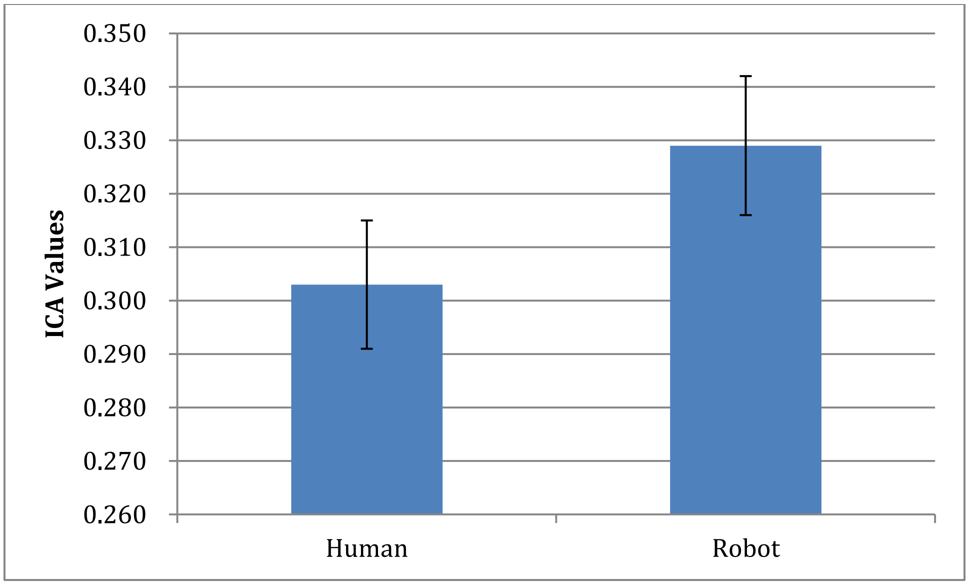

Figure 29: Mean ICA Values by Type

Entity was found to have a significant effect on ICA [F(3, 132) = 9.04, p = 0.001]. Participants had a significantly higher ICA value for Robot 1 (M = 0.32, SD = 0.09) than Human 1 (M = 0.29, SD = 0.09), and a significantly higher ICA value for Robot 2 (M = 0.33, SD = 0.09) than Human 1 (M = 0.29, SD = 0.09) and Human 2 (M = 0.31, SD = 0.08). Participants also had a significantly higher value for ICA for Human 2 (M = 0.31, SD = 0.08) than Human 1 (M = 0.29, SD = 0.09).

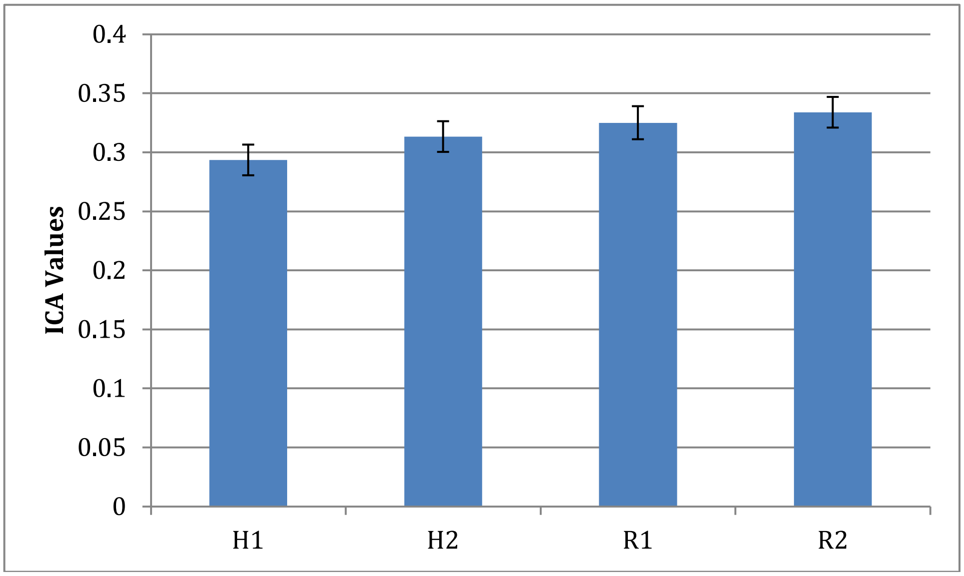

Figure 30: Mean ICA Values for each Entity

Size Effects

NASA-TLX Performance Subscale

Significant main effects were found for *size* for the NASA-TLX Performance Subscale [F(1, 52) = 9.26, *p* = 0.004]. Participants scored Performance significantly higher (meaning that they believed they performed worse) for the large entities (Human 1, Robot 1; *M* = 30.09, *SD* = 20.81) than the small entities (Human 2, Robot 2; *M* = 24.53, *SD* = 17.08).

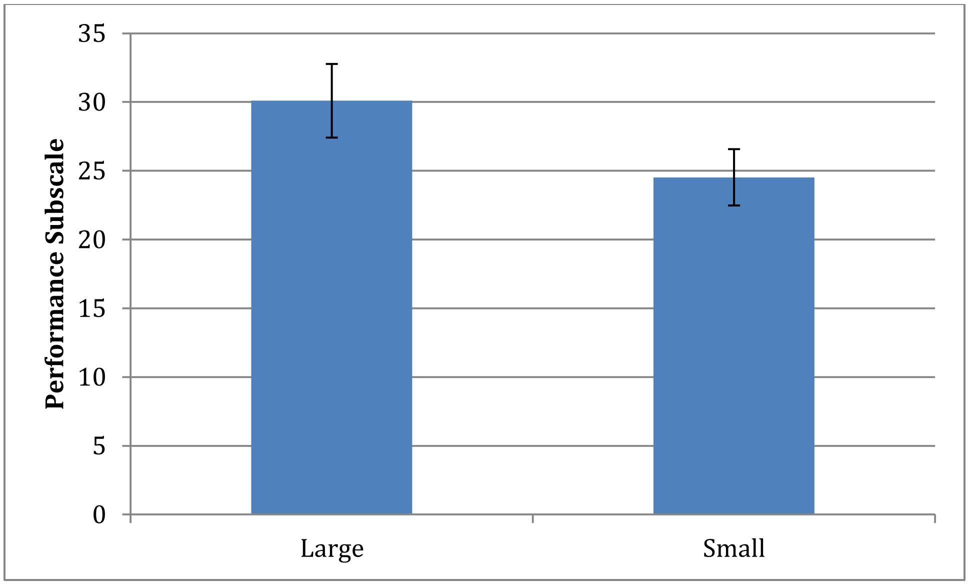

Figure 31: Mean Values for the NASA-TLX Performance Subscale for each Size

<u>Performance Subscale</u>

Significant main effects were found for the Performance Subscale [F(2.51, 130.72) = 4.03, *p* = 0.013]** across *entity*. Participants scored Performance significantly higher (meaning that they believed they performed worse) for Human 1 (*M* = 29.53, *SD* = 22.50) and Robot 1 (*M* = 30.66, *SD* = 19.10) than Human 2 (*M* = 23.68, *SD* = 19.20). And scored Performance significantly higher (meaning that they believed they performed worse) for Robot 1 (*M* = 30.66, *SD* = 19.10) than Robot 2 (*M* = 25.38, *SD* = 14.90).

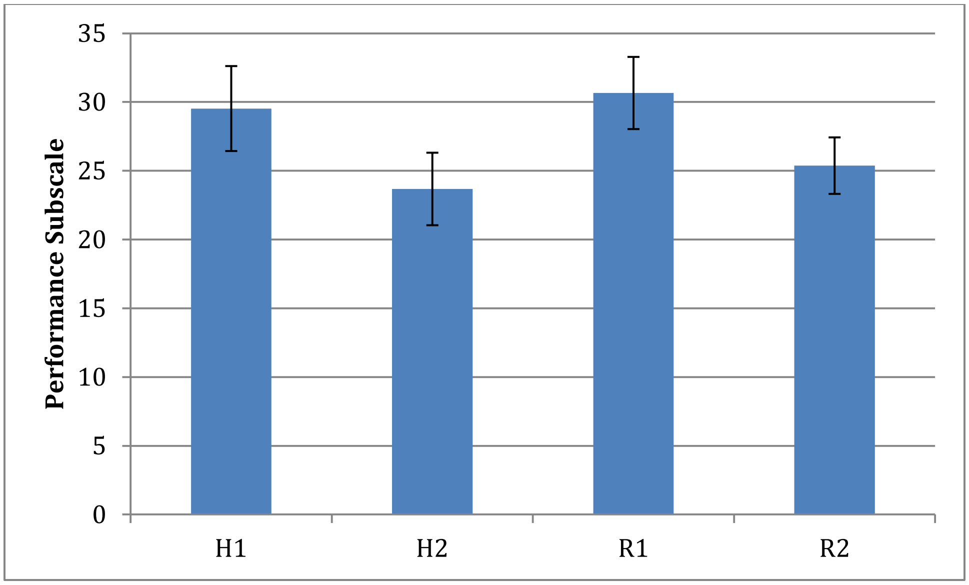

Figure 32: Mean Values for the NASA-TLX Performance Subscale for each Entity

Index of Cognitive Activity

Significant main effects were found for *size* for the ICA [F(1, 44) = 6.21, $p = 0.017$]. Participants had significantly higher ICA values for the small entities (Human 2, Robot 2; M = 0.324, SD = 0.09) than the large entities (Human 1, Robot 1; M = 0.309, SD = 0.09).

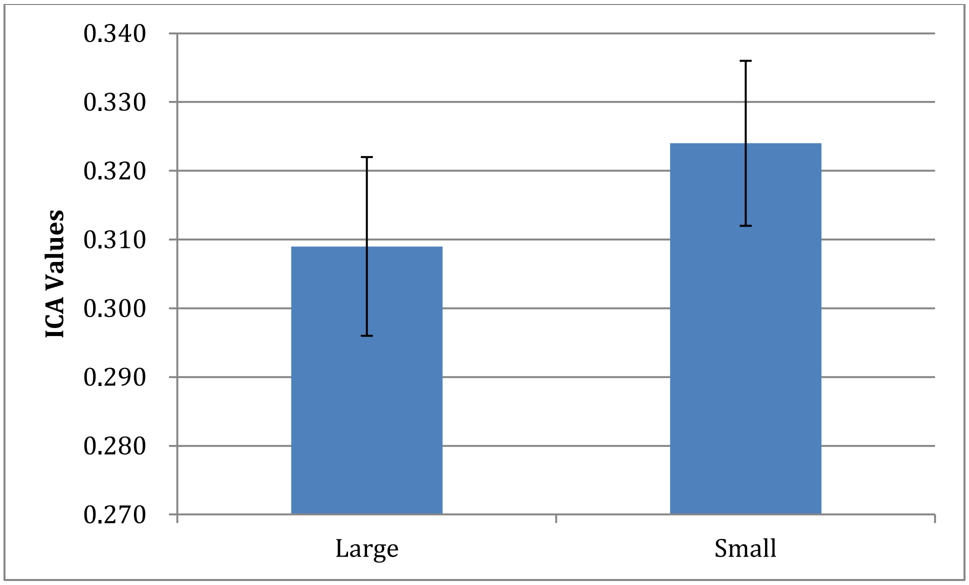

Figure 33: Mean ICA Values for each Size

CHAPTER FIVE: CONCLUSION

Hypothesis H1

Summary of Results

Hypothesis H1, which predicted that participants would have no difference in objective performance measures, was not supported by the empirical data. Participants scored significantly higher for Human videos than for Robot videos.

Discussion

Although participants scored significantly higher for Human (84%) than for Robot (82%) videos, both scores were above 80%. This shows that participants had a high chance of accurately interpreting the cues of both entity types. However, the difference was significant between the two. Regardless of entity type, participants scored lower on the less salient implicit communications (patrolling and investigating), and higher for the more salient (hiding and retreating), for each entity. This shows that communication saliency may not depend on entity. Since one human entity outperformed one robot and one robot also outperformed one human, it can be argued that humans can successfully interpret implicit cues from any entity. There was also an increase in performance based on scenario order. The primary struggle of correctly labeling an action occurred during Scenario 1, effectively making Scenario 1 a training scenario. The actual training task that participants underwent did not include any of the executed implicit communications. So, participants saw the implicit actions for the first time during Scenario 1.

After each participant saw the behaviors, regardless of entity, they were able to properly assign those movements to the proper category. This shows that learning of certain behaviors can occur across any entity. This is further supported by the fact that participants who viewed human videos prior to robot videos showed an increase in performance for successive scenarios, as did participants who saw robot videos first. Also, the lack of significant difference between groups who saw robots or humans first implies that performance was relatively identical regardless of entity.

A limitation of the study was the limited amount of answer choices. Allowing participants to write in all answers might have revealed more significant differences, but would have also lengthened the study. Even when participants selected "other", most chose an answer synonymous with the expected answer, such as scanning or looking, for investigating.

Hypothesis H2

Summary of Results

Hypothesis H2, which predicted that participants would have no difference in subjective performance measures, was not supported by the empirical data. Participants were consistently, significantly more confident in answer choices for Human videos than for Robot videos.

Discussion

Unsurprisingly, participants reported more confidence during human videos than robot videos. Human participants have more experience interacting with humans than with robots.

Even when robots performed identical movements, the participants were more confident in their answers for the human entities. This was also the case for the more salient implicit communications, and one of the less salient implicit communications (patrolling). However, there was no significant difference for the least salient implicit communication (investigating). Humans are more comfortable communicating with humans (Breazeal, 2004), but as experience interacting with robots produces more expertise, this difference could subside. It is also important to note that even though answer choices were limited, participants still showed more confidence in their answers for humans. Finally, when robot entities resulted in higher objective scores than a human entity, robots maintained lower levels of subjective confidence.

Hypothesis H3

Summary of Results

Hypothesis H3, which predicted that participants would report no difference in subjective workload between video types, was not supported by the empirical data. Participant's responses resulted in no significant differences for the DSSQ or the NASA-TLX.

Discussion

Subjective load is correlated to the cost of the task to the operator (Averty, Collet, Dittmar, Athenes & Vernet-Maury, 2004). Since the tasks were designed to be equal across entities, they were of equal cost to the participants. Most likely, participants exerted identical levels of cognitive effort in interpreting, and labeling, the cues of each entity type.

Hypothesis H4

Summary of Results

Hypothesis H4, which predicted that participants would demonstrate no difference in physiological responses associated with increased workload while viewing robot videos versus human videos was only partially supported by the empirical data. Robot videos had significantly higher values for ICA than Human videos. However, differences in the engagement index across entities were insignificant. Participants also had significantly lower HRV for Human videos than for Robot videos.

Discussion

Lower HRV has been shown to reveal increased levels of workload (Fairclough, Venables & Tattersall, 2004). However, HRV has been analyzed across certain bandwidths, as bandwidths have varying responses to increased workload (Fairclough et al., 2004). The system used for this experiment totaled HRV across each bandwidth so it is unclear how the bands responded individually.

Task difficulty was identical across entities. Apparently, the engagement level did not require a change based on entity, since the task had not changed (Freeman, Mikulka, Scerbo, Prinzel & Clouatre, 2000). Participant engagement level settled into a range and most likely stayed in that range regardless of entity.

But the ICA values reveal increased cognitive effort during the robot videos. Perhaps this workload response was based on learning since the participants were unfamiliar with the robots.

Learning has been shown to demonstrate physiological workload responses (Faircloug et al., 2004; Coyne, Baldwin, Cole, Sibley & Roberts, 2009). The participants may also have been paying more attention to the robots, resulting in increased mental effort. Pupil dilation can also be the result of ambient light (De Greef, Lafeber, Oostendorp & Lindenberg, 2009). A limitation of the study is that the robots, due to their heights, were lower on the screen than humans. So the change in pupil diameter may have resulted from a change in eye position relative to light on the screen or in the laboratory. Mental demand has been shown to decrease with experience (Fairclough et al., 2004) but robot ICA was higher than humans regardless of scenario order. Differences may have been the result of a change in strategy for robots or a reduction of cognitive effort in humans (Marshall et al., 2002).

Conclusions

Fong, Thorpe, and Baur (2003) suggested that research should focus on how human and robot entities "influence each other", which assumes that humans are influenced by their perception of robotic behavior. There is evidence to support this, since humans had increased ICA values for robots. Although this experiment only taxed one channel of cognitive resources, there is still evidence to support an increase in the demand of that channel while viewing robot videos.

Increased autonomy is viewed as the answer to the mental workload problem. But between supervisory control and full autonomy, a great chasm exists. And it remains unclear how working alongside robots will affect the human cognitively. Controlling and supervising robots is a top-down relationship, but operating in proximity to a robot is a side-by-side relationship that has rarely been investigated. Further evaluation is necessary in order to understand how humans will work with robots as peers.

Implicit communication should be evaluated at all levels of autonomy as an additional modality of communication. Just as adaptive automation has benefits, adaptive communication may benefit teammates as well. Since physiological measures are being researched to make robots aware of human state (Rani & Adams, 2007), it may be beneficial for explicit communication to trigger if the human shows a spike in cognitive activity, similar to adaptive automation shifts based on cognitive load (Freeman et al., 2000).

Future Research

Kiesler & Goetz (2002) evaluated humans' mental models of robots related to the sociability, intellect, and personality of the robot. These attributes are important in areas where robots behave in a more humanlike manner. In order to balance the one-sidedness of research regarding this relationship, more work is needed to develop the human mental model of robot behavior and also focus on the intent of robot behavior based on observed actions. Having the ability to properly interpret robotic behavior will allow humans to infer intent from those actions, which is the case when observing human behavior. Brooks (2007) suggested that just as humans construct mental models of one another based on abilities and intentions; humans will also construct mental models of robots based on the robot's abilities and intentions.

Future research should evaluate human decision-making based on implicit cues of a robot. It is one thing to label the implicit nature of an action, but it is quite another to make decisions based on the cues of an autonomous robot teammate. Using similar movements such as those used in this study in the context of a simulated battlespace should reveal how human behavior differs when receiving cues from humans versus robots.

Application

Research has evaluated how anthropomorphic features enhance communication between humans and robots (Blow, Dautenhahn, Appleby, Nehaniv & Lee, 2006; Bruce, Nourbakhsh & Simmons, 2002; O'Brien, Sutherland, Rich & Sidner, 2011; Powers & Kiesler, 2006; Waldherr, Romero & Thrun, 2000), but practical actions have not been explored as often (Giardini & Castelfranchi, 2004). The perception of the action is the most important aspect implicit communication. Unnoticed, invisible, or misinterpreted actions break down the communicative intent of the actions being performed. This results in delayed goal accomplishment, delayed communication, or reverting back to explicit communication modalities. Castelfranchi (2009) suggested that teammates interacting in a proximate location would incorporate implicit communication into their collaboration and develop it as they become more experienced in their interaction. The dynamic nature of the operational environment requires soldiers to perform simultaneous tasks with little room for error (Muth, Kruse, Hoover & Schmorrow, 2006). Mental resources are occupied with military operations, and do not need to be spent interpreting robotic actions (Gillian et al., 2010). Once the mental model of robotic behavior is solidified, human teammates should be able to operate alongside robots as viable social partners. However, familiarity with this relationship should not occur in the field. Long-term improvements to HRI should increase a robot's utility, increase team performance, and reduce stress on human teammates (Evans & Jentsch, 2010).

APPENDIX A: DEMOGRAPHICS QUESTIONNAIRE

Demographics Questionnaire

Participant # _______ Age ______ Major ________________ Date ___________ Gender ___

1. What is the <u>highest</u> level of education you have had?
Less than 4 yrs of college ____ Completed 4 yrs of college ____ Other ____

2. When did you use computers in your education? (<u>*Circle all that apply*</u>)

Grade School	Jr. High	High School
Technical School	College	Did Not Use

3. Where do you currently use a computer? (<u>*Circle all that apply*</u>)
Home Work Library Other________ Do Not Use

4. How many hours per day do you use a computer? ___________

5. For each of the following questions, <u>circle</u> the response that best describes you.

How often do you:	
Use a mouse?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use a joystick?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use a touch screen?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use icon-based programs/software?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use programs/software with pull-down menus?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use graphics/drawing features in software packages?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use E-mail?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Operate a radio controlled vehicle (car, boat, or plane)?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Play computer/video games?	Daily, Weekly, Monthly, Once every few months, Rarely, Never

6. Which type(s) of computer/video games do you most often play if you play at least once every few months?

7. Which of the following best describes your expertise with computers? (check √ one)
_____ Novice
_____ Good with one type of software package (such as word processing or slides)

_____ Good with several software packages
_____ Can program in one language and use several software packages
_____ Can program in several languages and use several software packages

8. How many hours per day do you watch television? ________

9. How many hours per day do you spend reading? __________

10. Are you in your usual state of health physically? YES NO
If NO, please briefly explain:

11. How many hours of sleep did you get last night? ______ hours

12. What is your occupation? _______________

13. How often do you feel eye strain?

0	1	2	3	4	5
Not at all	Mildly		Average		Highly

14. During an average work day, do you feel that you focus on near objects (about 2 meters away) more than objects that are far away (6 meters or more)?

1	2	3	4	5
Strongly disagree		Agree		Strongly agree

APPENDIX B: RESTRICTIONS CHECKLIST

Participant #: Date:
Start time:

Restrictions Checklist

	Yes	No
Are you 18-40 years old?		
Have you had any caffeine in the last 2 hours?		
Have you had any nicotine in the last 2 hours?		
Have you had any Alcohol in the last 24 hours?		
Have you had any sedatives or tranquilizers in the last 24 hours?		
Have you had any aspirin, Tylenol, or similar medications in the last 24 hours?		
Have you had any antihistamines or decongestants in the last 24 hours?		
Have you had any anti-psychotics or anti-depressants in the last 24 hours?		
Is your hair wet?		
Do you have woven or artificial hair?		
Are you pregnant?		
Do you have any metal plates in your head?		
Are you color blind?		
Do you have normal or corrected to normal vision?		
Do you have a history of epilepsy or seizures?		

	Left	Right	Either
Do you have any impairment of your dominant arm or hand?			
Are you right handed?			
Which hand do you use to write with?			
Which hand do you use to throw a ball?			
Which hand do you hold a toothbrush with?			
Which hand holds a knife when you cut things?			
Which hand holds a hammer when you nail things?			

APPENDIX C: DUNDEE STRESS QUESTIONNAIRE PRE-TEST

QUESTIONNAIRE

General Instructions

This questionnaire is concerned with your feelings and thoughts at the moment. Please answer **every** question, even if you find it difficult. Answer, as honestly as you can, what is true of you. Please do not choose a reply just because it seems like the 'right thing to say'. Your answers will be kept entirely confidential. Also, be sure to answer according to how you feel **AT THE MOMENT**. Don't just put down how you usually feel. You should try and work quite quickly: there is no need to think very hard about the answers. The first answer you think of is usually the best.

For each statement, circle an answer from 0 to 4, so as to indicate how accurately it describes your feelings **AT THE MOMENT**.

Definitely false = 0, Somewhat false = 1,
Neither true nor false = 2, Somewhat true = 3, Definitely true = 4

1. The content of the task will be dull.	0	1	2	3	4
2. I feel relaxed.	0	1	2	3	4
3. I am determined to succeed on the task.	0	1	2	3	4
4. I feel tense.	0	1	2	3	4
5. Generally, I feel in control of things.	0	1	2	3	4
6. I am reflecting about myself.	0	1	2	3	4
7. My attention is directed towards the task.	0	1	2	3	4
8. I am thinking deeply about myself.	0	1	2	3	4
9. I feel energetic.	0	1	2	3	4
10. I am thinking about something that happened earlier today.	0	1	2	3	4
11. I will find the task too difficult for me.	0	1	2	3	4
12. I will find it hard to keep my concentration on the task.	0	1	2	3	4
13. I am thinking about personal concerns and interests.	0	1	2	3	4
14. I feel confident about my performance.	0	1	2	3	4
15. I am examining my motives.	0	1	2	3	4
16. I feel like I could handle any difficulties I encounter.	0	1	2	3	4
17. I am motivated to try hard at the task.	0	1	2	3	4
18. I am thinking about things important to me.	0	1	2	3	4
19. I feel uneasy.	0	1	2	3	4
20. I feel tired.	0	1	2	3	4

APPENDIX D: DUNDEE STRESS QUESTIONNAIRE POST-TEST

QUESTIONNAIRE

<u>General Instructions</u>

This questionnaire is concerned with your feelings and thoughts while you were performing the task. Please answer **every** question, even if you find it difficult. Answer, as honestly as you can, what is true of you. Please do not choose a reply just because it seems like the 'right thing to say'. Your answers will be kept entirely confidential. Also, be sure to answer according to how you felt **WHILE PERFORMING THE TASK**. Don't just put down how you usually feel. You should try and work quite quickly: there is no need to think very hard about the answers. The first answer you think of is usually the best.

For each statement, circle an answer from 0 to 4, so as to indicate how accurately it describes your feelings **WHILE PERFORMING THE TASK**.

Definitely false = 0, Somewhat false = 1,
Neither true nor false = 2, Somewhat true = 3, Definitely true = 4

1. The content of the task was dull.	0	1	2	3	4
2. I felt relaxed.	0	1	2	3	4
3. I was determined to succeed on the task.	0	1	2	3	4
4. I felt tense.	0	1	2	3	4
5. Generally, I felt in control of things.	0	1	2	3	4
6. I reflected about myself.	0	1	2	3	4
7. My attention was directed towards the task.	0	1	2	3	4
8. I thought deeply about myself.	0	1	2	3	4
9. I felt energetic.	0	1	2	3	4
10. I thought about something that happened earlier today.	0	1	2	3	4
11. I found the task too difficult for me.	0	1	2	3	4
12. I found it hard to keep my concentration on the task.	0	1	2	3	4
13. I thought about personal concerns and interests.	0	1	2	3	4
14. I felt confident about my performance.	0	1	2	3	4
15. I examined my motives.	0	1	2	3	4
16. I felt like I could handle any difficulties I encountered.	0	1	2	3	4
17. I was motivated to try hard at the task.	0	1	2	3	4
18. I thought about things important to me.	0	1	2	3	4
19. I felt uneasy.	0	1	2	3	4
20. I felt tired.	0	1	2	3	4

APPENDIX E: NASA TASK LOAD INDEX

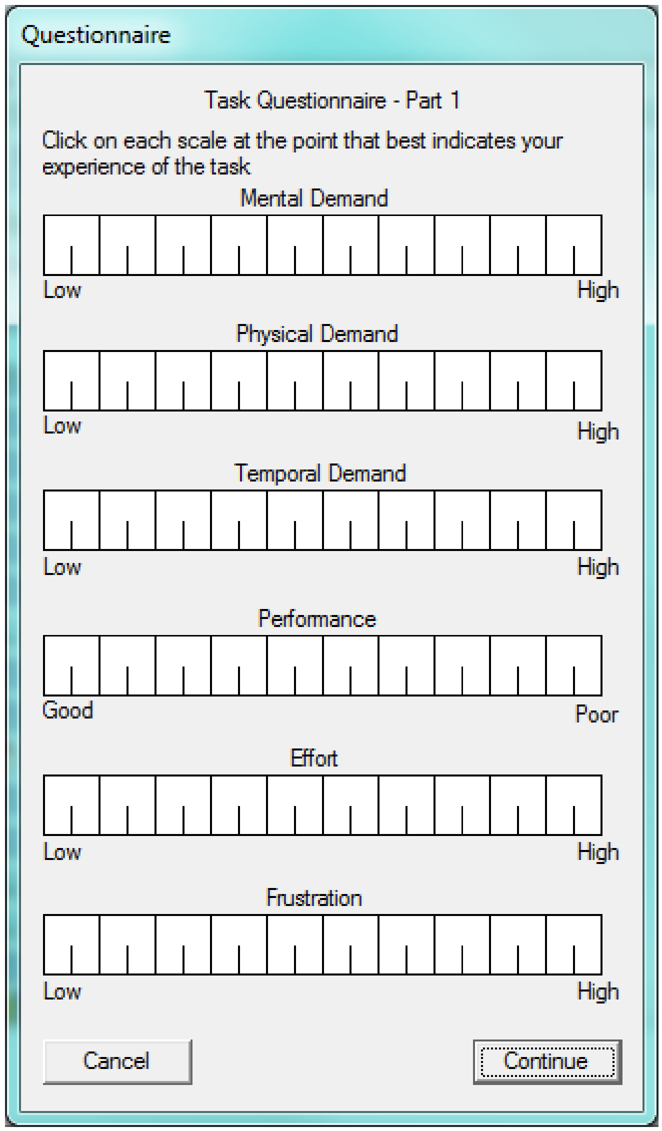

Figure 34: Part 1 of the NASA-TLX Computer Program

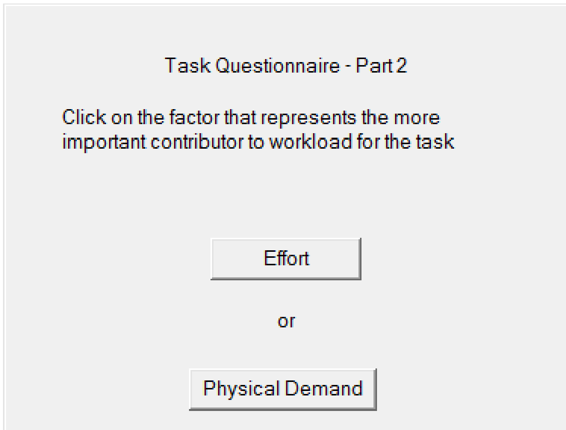

Figure 35: Part 2 of the NASA-TLX Computer Program

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