Exploratory Factor Analysis of Robot Social Intelligence

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Abstract

Social intelligence is the ability to interact effectively with others in order to accomplish goals (Ford & Tisak, 1983). Because social robots are designed to interact and communicate with humans, it is important that they exhibit social intelligence (Dautenhahn, 2007). Robots are designed to do a variety of things, including building relationships with people, learning things from people, assisting humans in completing tasks, and teaching people. In order to be effective, robots should avoid interfering with tasks that are being done by people; social intelligence helps them do this. The purpose of this research was to examine the factor structure of the 20 Perceived Social Intelligence (PSI) Scales. 295 adults (145 female, 150 male) were recruited using Amazon's MTurk for a 2-hour online study paying $15. Participants were asked to watch videos of human-robot interactions (HRI) and indicate whether they thought the robots possessed 20 aspects of social intelligence using a 5-point agreement scale. Three factors were extracted from the PSI Scales: Mental Interpretation, Approachability, and Behavioral Interpretation. Men obtained higher factor scores on Approachability; however, the gender differences were small.

Introduction

Social intelligence is important when interacting with others because it allows individuals to assess social situations they find themselves in and adapt accordingly. Ford and Tisak (1983) describe social intelligence as the ability to interact effectively with others in order to accomplish goals. Not only does social intelligence pertain to human-human interactions, it also improves human-robot interactions (HRI) by making social exchanges smoother, thus facilitating goal achievement. Some robots are designed to be more socially intelligent than others, as they are used in roles where they interact and communicate with humans (Dautenhahn, 2007). For example robots are being used as teachers, social companions, and even medical assistants.

The Perceived Social Intelligence (PSI; Barchard, Lapping-Carr, Westfall, Banisetty, & Feil-Seifer, 2018) Scales assess 20 different aspects of robot social intelligence and can be used to assist in the development of socially intelligent robots. Roboticists can determine which robot behaviors, functions, and features are associated with higher social intelligence in different environments, for different tasks, and when working with different types of people. Better social intelligence might lead to more effective human robot interaction (HRI) by allowing humans and robots to complete their shared goals more easily. The purpose of this research was two-fold: first, to explore the factor structure of the PSI scales; second, to begin exploring how perceptions of social intelligence vary by comparing scores on these factors for men and women.

Method

Participants

Participants were recruited using Amazon's MTurk for a 2-hour online study paying $15. To improve data quality, we restricted participant locations to the United States using both MTurk (which requires a US social security number to register) and Qualtrics (whose location screening is based upon IP addresses). To further improve data quality, we restricted participants to MTurk workers who had completed at least 500 HITS and had a minimum acceptance rate of 95%. In addition, we assigned each participant a qualification to ensure that they could not participate more than once.

In order to ensure that participants would be able to view our videos properly, we also screened the devices they used. They had to use a computer (not a cell phone), and they had to be able to hear audio. Participants had to listen to one of 10 sounds (e.g., chicken, train, dog) and then identify which sound it was. Given our screens, we are confident in the quality of our participants.

Our final sample was 295 adults (145 female, 150 male). They ranged in age from 19 to 72 (M = 37.39, SD = 11.50). 80.4% of participants identified themselves as White , 7.1% identified as African-

American, 5.1% identified as Asian, 4.1% identified as Hispanic, 0.3% identified as Native American, and 3.0% identified as other.

Procedure

Participants completed the study online. After consenting to participate, participants completed questions about demographics and their background with robots. Next, participants viewed five videos, each of which showed a robot interacting with people. Immediately after each video, they completed several measures regarding their impressions of the robot. Finally, participants were debriefed and compensated for their time.

Materials

Videos. Five videos (1-3 minutes long) depicting human-robot interactions were selected to represent a wide range of robot social intelligence. We received permission from the videos' authors to both use and edit these videos for the current study. The videos were shown in the following order. Robovie, a large humanoid robot, asks a woman to lie about seeing an aquarium on her tour of a research lab; the woman agrees and is shown lying to the robot's supervisor (Kahn et al., 2015). NAO, a small humanoid robot, performs community service for shoplifting batteries, apparently to no effect as the NAO then steals batteries from a friend's bike light, resulting in a crash (de Greeff et al., 2014). A robotic ottoman encourages people to put their feet up and cues them that it wants to leave (Sirkin, Mok, Yang, & Ju, 2015). PR2, a large, boxy, humanoid robot, works cooperatively with two different people to stack blocks in specific patterns, adjusting its behavior based upon unexpected human behaviors (Devin, Clodic, & Alami, 2017). Dragonbot, a small, fluffy, toy dragon robot, takes turns telling stories with children and creating visual depictions of the stories on an iPad (Kory, 2014).

Table 1

Perceived Social Intelligence Scales, Definitions, and Best Items

Scale Name	Definition	Single Best Item
	The robot appears…	This robot…
Social Competence	to have strong social skills.	is socially competent.
Recognizes Human Emotions	to detect people's emotions.	recognizes human emotions.
Recognizes Human Behaviors	to detect people's behaviors.	notices when people do things.
Recognizes Human Cognitions	to detect people's cognitions.	can figure out what people think.
Adapts to Human Emotions	to adapt its behavior based on people's emotions.	responds appropriately to human emotion.
Adapts to Human Behaviors	to adapt its behavior based on people's behaviors.	adapts effectively to different things people do.
Adapts to Human Cognitions	to adapt its behavior based on people's cognitions.	adapts its behavior based on what people around it know.
Predicts Human Emotions	to anticipate people's emotions.	anticipates others' emotions.
Predicts Human Behaviors	to anticipate people's behavior.	anticipates people's behavior.
Predicts Human Cognitions	to anticipate people's cognitions.	anticipates others' beliefs.
Identifies Humans	to detect human presence.	notices human presence.
Identifies Individuals	to identify and recognize people as individuals.	recognizes individual people.
Identifies Social Groups	to discern which people are with each other.	knows if someone is part of a social group.
Friendly	to enjoy social interactions.	enjoys meeting people.
Helpful	to willingly assist in tasks.	tries to be helpful.
Caring	to care about the well-being of others.	cares about others.
Trustworthy	deserving of trust.	is trustworthy.
Rude	rude and disrespectful.	is impolite.
Conceited	overly proud of itself or its abilities.	thinks it is better than everyone else.
Hostile	antagonistic and violent.	tries to hurt people.

Note. This table was adapted from the Perceived Social Intelligence (PSI) Scales Test Manual (Barchard et. al., 2018).

Measures

Demographic variables. Participants completed items asking them for their sex, age, ethnicity.

Ratings of each robot. The Perceived Social Intelligence (Barchard et. al., 2018) Scales measure the extent to which robots are perceived as possessing 20 aspects of social intelligence. See Table 1. Each scale is measured using four items. Participants indicate the extent to which they agree that each item describes a particular robot using a 5-point agreement scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. To reduce possible order effects and carry-over effects in our study, we presented the 80 PSI items in a different order for each of the five robots.

Data Analysis

A principal component analysis was used to analyze the data. Five criteria were considered to determine the number of factors in this dataset: number of factors based on theory, Kaiser-Guttman rule (Cliff, 1988), scree test (Zwick & Velicer, 1986), parallel analysis (Horn, 1965; Cota, Longman, Holden, & Rekken, 1993), and the minimum average partial test (MAP test; Velicer, 1976).

Table 2

Factor Analysis Results for Rotated Factors

Item	Factor 1	2	3	h^2
Recognizes Human Emotions	**.94**	.03	.01	.90
Adapts to Human Emotions	**.93**	.08	-.05	.87
Predicts Human Emotions	**.91**	-.05	.08	.87
Predicts Human Cognitions	**.91**	-.09	.01	.81
Identifies Social Groups	**.88**	-.19	.07	.77
Socially Competent	**.83**	.14	.06	.81
Identifies Individuals	**.82**	-.08	.09	.71
Recognizes Human Cognitions	**.81**	-.06	.23	.83
Adapts to Human Cognitions	**.77**	.13	.20	.82
Conceited	.04	**-.88**	-.07	.81
Rude	-.09	**-.86**	-.13	.88
Hostile	.14	**-.86**	-.16	.80
Trustworthy	.21	**.76**	.02	.71
Helpful	.16	**.64**	**.35**	.78
Caring	**.74**	**.47**	-.13	.83
Friendly	**.60**	**.47**	.01	.71
Recognizes Human Behaviors	.08	.02	**.90**	.88
Adapts to Human Behaviors	.20	.10	**.76**	.79
Identifies Humans	.14	.16	**.68**	.65
Predicts Human Behaviors	**.62**	-.02	**.44**	.76
Factor Intercorrelations	1	2	3	
Factor 1	1.00	.22	.37	
Factor 2		1.00	.29	
Factor 3			1.00	

Note. h^2 = communality. Salient factor pattern matrix coefficients are in boldface. All items in Factor 2 were reverse scored. Factor 1 = Mental Interpretation. Factor 2 = Approachability. Factor 3 = Behavioral Interpretation.

Based upon the test design, we predicted that the PSI Scales would have six factors.. However, Kaiser-Guttman criteria, scree test, and parallel analysis suggested there were three factors. The MAP test suggested four factors.

We extracted three factors from this dataset because the Kaiser-Guttman rule, scree test, and parallel analysis tests suggested there were three factors. Additionally, because the Kaiser-Guttman rule typically overestimates the number of factors in a dataset (Cliff, 1988),it is unlikely that we have four or six factors as suggested by the MAP test and estimation based on theory, respectively.

After examining several oblique and orthogonal rotations we selected the direct oblimin rotation with a delta value of -1 as the optimal rotation. This rotation was selected because it had a high hyperplanar count (21), a low number of complex variables (4), and a moderate average interfactor correlation (.29).

Results

The factor loadings and inter-factor correlations are given in Table 2. Factor 1 was named Mental Interpretation because it suggested that the robot was able to interpret the cognitions and emotions of humans. It had positive salient coefficients on the following PSI scales: Adapts to Human Cognitions, Adapts to Human Emotions, Recognizes Human Emotions, Predicts Human Cognitions, Predicts Human Emotions, and Recognizes Human Cognitions.

Factor 2 was named Approachability. The following PSI scales had negative salient coefficients: Conceited, Rude, and Hostile. It also included the following PSI scales with positive salient coefficients: Friendly, Helpful, Trustworthy, and Caring. The Approachability factor suggests that the robot has wanted characteristics and does not have unwanted characteristics that humans may appreciate in a social companion.

Factor 3 was named Behavioral Interpretation. The following PSI scales had positive salient coefficients on this factor: Adapts to Human Behaviors, Recognizes Human Behaviors, Identifies Humans, and Predicts Human Behaviors. These variables are centered on interpreting human behaviors.

Factor scores were calculated using the regression method, and then men and women were compared on those factor scores. Men obtained significantly higher factor scores on the Approachability factor $t(239) = -1.98$, $p = .049$), though the differences were very small. See Table 3.

Discussion

Our analysis indicated three factors were present in the perception of robot social intelligence: Mental Interpretation, Approachability, and Behavioral Interpretation. Mental Interpretation focuses on the robot's capacity to recognize human emotions and cognitions. Approachability seemed to suggest the traits necessary for a desirable social

Table 3

Means (and Standard Deviations) for Men and Women on Each Factor

Factor	Men	Women	t-test
1	.57(.77)	.69(.70)	$t(239) = -1.26$, $p = .208$
2	.10(.71)	.28(.69)	$t(239) = -1.98$, $p = .049$
3	-.10(.87)	.06(.72)	$t(239) = -1.6$, $p = .111$

Note. Factor 1 = Mental Interpretation. Factor 2 = Approachability. Factor 3 = Behavioral Interpretation.

partner. Behavioral Interpretation is centered on interpreting behaviors in humans. Mental Interpretation seems to assess whether robots can make accurate judgments about humans' internalized thought processes. Behavioral Interpretation, seems to assess whether robots can make accurate judgments about humans' externalized behaviors.

An understanding of these three factors could guide roboticists to develop more desirable social robot companions. Rather than using each of the 20 PSI scales to describe the perceived social intelligence of robots, roboticists could focus on these three factors, simplifying the research. Researchers could explore the robot features, functions, and behaviors that change perceptions that robots have these three different aspects of social intelligence. Moreover, researchers could explore whether these three aspects of social intelligence vary across environments, robot tasks, and the people they are interacting with.

Gender differences were found in this dataset. Men obtained higher factor scores on Approachability; however this difference was small. Therefore, we do not recommend that roboticists design robots differently for men and women.

Future research could look for differences across cultures and age groups. For example, people living in societies that emphasize personal space might rate robots differently on Approachability than people from societies that do not. This study only examined individuals from the United States. Future research should include and compare participants from other countries. Additionally, researchers could look at how age influences perception of robot social intelligence. There might be differences in perceptions of social intelligence between older and younger individuals. This study had a mean age of ~37 years. Studies investigating how younger or older adults perceive robot social intelligence might find significant differences. Furthermore, children at different developmental states might also perceive robot social intelligence differently. Research on age differences might be useful when developing social robot teachers and medical robots.

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