What the Factor(s)!?: Perceptions of Social Intelligence in Robots

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Author Note: The authors thank the National Science Foundation (IIS-1719027) and the Nevada Space Grant Consortium (NNX15AK48A) for their support of this research.

Reference: Helm, M. R., Cadenas Santos, J. A., Denecker, L. L., Huang, Y., Barchard, K. A., Lapping-Carr, L., Westfall R. S., Feil-Seifer, D. (2020, April). *What the factors(s)!?: Perceptions of social intelligence in robots.* Poster presented at the Western Psychological Association conference in San Francisco, CA.

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Abstract

Social robots designed to be companions, assistants, and teachers might interact more effectively with humans if they are socially intelligent. Previous research assessed people's perceptions of robots' social intelligence but did not analyze the factors for these perceptions. The present study sought to determine the factors that underlie the Perceived Social Intelligence (PSI) of robots. Based on previous research, we hypothesized four factors: social presentation, emotion, cognition, and behavior.

Two hundred and ninety-six adult MTurk workers (150 male, average age 37) viewed five videos in which a person interacts with a robot and rated these robots on the 20 PSI Scales. These scales measure overall social intelligence; the abilities to (1) recognize, (2) adapt to, and (3) predict human (a) emotions, (b) behaviors, and (c) cognitions; to identify humans, individuals, and social groups; and to present oneself as a desirable social partner: someone who is friendly, helpful, caring, and trustworthy, and who is not rude, conceited, or hostile.

Based upon the scree test, parallel analysis, and MAP test, we extracted three factors. Several different rotations were examined. Based upon the number of complex scales, the hyperplanar count, and the extent of correlation among the factors, the direct oblimin rotation with delta -1 was selected.

The first factor, Theory of Mind, measures a robot's ability to recognize, predict, and adapt to the emotions and cognitions of humans. The second factor, Approachable Disposition, measures the extent to which the robot was perceived as being friendly, trustworthy, caring, and helpful and not conceited, hostile, and rude. The third factor, Reasoning about Behavior, measures the ability to recognize, predict, and adapt to human behavior.

In future research, the first factor might divide into two (as originally hypothesized) if robots were selected so that the ones that are skilled with emotions are not the ones that are skilled with cognitions. The number of factors may be important because roboticists who are trying to design better robots may want to focus on one particular factor.

Introduction

Decades ago personal robots only occupied the spaces of science fiction and imagination, but in today's tech-savvy world, people are finding new ways to design and use them. With sales of personal robots for home use increasing, more sophisticated robots designed to provide solutions beyond simple household chores are becoming more popular (Hägele, 2018). Socially isolated individuals and populations might benefit from owning a personal or service-oriented robot (Khosravi, Rezvani, & Wiewiora, 2016). Recently, robots have been developed for persons who suffer from neurodegenerative diseases such as dementia and Alzheimer's disease (Pino, Boulay, Jouen, & Rigaud, 2015). Robots have also been developed to teach and entertain (Edwards, Edwards, Stoll, Lin, & Massey, 2018; Peters, Broekens, & Neerincx, 2017; Shahid, Krahmer, & Swerts, 2014). Additionally, there is evidence to suggest that a robot could act as a welcome social surrogate when a human companion is unavailable (Shahid et al., 2014). Robots are even being employed for use in adult care facilities to help residents with daily activities and staying healthy (Vandemeulebroucke, Dierckx de Casterlé, & Gastmans, 2018). These robots are different from other robots in their ability to interact with humans in both physical and social environments and are therefore considered social robots (Dautenhahn, 2007b).

The ability to decode and interpret social information relates to the concept of social intelligence (Barnes & Sternberg, 1989). Social Intelligence (SI) is the ability to understand and manage social relationships (Thorndike, 1920). Further attempts to understand SI reveal it is comprised of cognitive abilities (understanding, remembering, knowledge) and noncognitive behaviors (eye contact, speech, body posture) that are required for socially competent behavior (Conzelmann, Weis, & Süß, 2013; Ford & Tisak, 1983).

One critical benefit of robots being social is enhanced human-robot interaction (HRI; de Greeff & Belpaeme, 2015). HRI is a growing area of study for researchers who seek to make the interaction between robots and humans more desirable and comfortable for humans (Dautenhahn, 2007a). The more engaging a robot is to humans, the more efficient the robot is perceived to be at doing its intended task (Peters et al., 2017). Social interactions can fail if one party is not interested in interacting. In HRI, humans choose whether to interact with robots. Therefore, to be perceived as socially desirable companions, robots must demonstrate social skills and behaviors similar to those found in human-human interactions. (Dautenhahn, 2007b; Edwards et al., 2018; Ruiz-Garcia, Elshaw, Altahhan, & Palade, 2018). While robots do not have actual SI, they can be perceived as having qualities like a mind and thus display perceived social intelligence (PSI; Abubshait & Wiese, 2017).

The present research seeks to investigate what factors underlie the PSI Scales, a recently developed measure that explores how robots are perceived as socially intelligent (Barchard, Lapping-Carr, Westfall, Banisetty, & Feil-Seifer, 2018). By better understanding the factors that underlie the PSI Scales, robot researchers can explore a robot's PSI utilizing a more parsimonious set of scores. In addition, knowing the factors that underlie the PSI Scales might allow robot manufacturers to design more socially adept robots by emphasizing the characteristics associated with each factor that could help the robot to fulfill its purpose. Furthermore, by understanding the factor structure of the PSI Scales, researchers can explore the factors found in this study in depth. Based upon the PSI Scales, we hypothesize that four factors will be found.

Method

Participants

A total of 296 (150 male, 145 female) participants completed this study. Participant ages ranged from 19 to 72 years old, averaging about 37 years old (M = 37.39, SD = 11.50). For additional participant demographic information, see Table 1.

Table 1

Participant Demographics

Characteristic	n	Percentage
Ethnicity		
White	238	80.41%
African-American	21	7.09%
Asian	15	5.07%
Hispanic	12	4.05%
Native American	1	0.34%
Other	9	3.04%
Gender		
Male	150	50.68%
Female	145	48.99%
Unidentified	1	0.34%
Total	296	100%

Measures

Demographics. Demographic information collected from participants included sex, age, and ethnicity.

PSI Scales. The PSI Scales (Barchard et al., 2018) measure 20 different aspects of social intelligence. Each scale contains 4 items for a total of 80 questions. Items are rated on a 5-point scale, where 1 = *Strongly Disagree*, 2 = *Disagree*, 3 = *Neutral*, 4 = *Agree*, and 5 = *Strongly Agree*. The questions were presented in a different order for each of the five robot videos. The score for each scale was computed by averaging the 4 items. For additional details of the scale items please see Table 2.

Table 2

PSI Scales, Descriptions, and Best Items

Scales	Description	Single best item for each scale
	This robot appears to…	This robot…
Recognizes Human Emotions	detect human emotions	recognizes human emotions.
Recognizes Human Behaviors	detect human behaviors	notices when people do things.
Recognizes Human Cognitions	detect human thoughts[b]	can figure out what people think.
Adapts to Human Emotions	adapt to human emotions	responds appropriately to human emotion.
Adapts to Human Behaviors	adapt to human behaviors	adapts effectively to different things people do.
Adapts to Human Cognitions	adapt to human thoughts[b]	adapts its behavior based upon what people around it knows.
Predicts Human Emotions	predicts human emotions	anticipates others' emotions.
Predicts Human Behaviors	predicts human behaviors	anticipates people's behavior.
Predicts Human Cognitions	predicts human thoughts[b]	anticipates others' beliefs.
Identifies Humans	detect human presence	notices human presence.
Identifies Individuals	identify individual humans	recognizes individual people.
Identifies Social Groups	identify groups of humans	knows if someone is part of a social group.
Social Competence	displays social skills	is socially competent.
Friendly	be friendly and sociable	enjoys meeting people.
Helpful	be helpful or considerate	tries to be helpful.
Caring	care about others	cares about others.
Trustworthy	be trustworthy	is trustworthy.
Rude [a]	be rude or disrespectful	is impolite.
Conceited [a]	be conceited or prideful	thinks it is better than everyone else.
Hostile [a]	be hostile or violent	tries to hurt people.

[a]Scales score needs to be reversed before computing the total scores. [b]Thoughts in this context refer to both thoughts and beliefs held by humans.

Procedures

Participants were recruited via MTurk and individually completed an unsupervised single session two-hour online survey. Participants were restricted to US residents and were only allowed to complete the survey once. Participants were required to have a minimum acceptance rate of 95% on MTurk, with at least 500 HITS completed. Devices of participants were screened to ensure participants were using computers rather than smart phones, so they could successfully watch the HRI videos presented in the survey. As an additional level of screening, participants were required to listen to and correctly identify one of ten sounds. This was done to ensure participants could hear audio.

During the study, participants were first asked for demographic information and about their previous experiences with robots. Participants then viewed and evaluated five robots depicted in videos of HRI. Following each video, participants responded to the questions comprising each of the 20 PSI Scales regarding their impressions of the robots featured in that video. After completing the study, participants were debriefed and compensated $15 for their time.

Data Analysis

To determine the number and nature of factors underlying the PSI Scales, a principal components analysis with multiple factors was conducted. To determine the number of factors, five criteria were considered: number of factors based on theory, the Kaiser-Guttman criteria (Cliff, 1988; Velicer, Eaton, & Fava, 2000), the scree test (Cattell, 1966), the minimum average partial (MAP) test (Velicer, 1976), and parallel analysis (Horn, 1965; Cota, Longman, Holden, & Rekken, 1993). Based upon theory, we predicted there would be four factors: social presentation, emotion, cognition, and behavior.

The Kaiser-Guttman criterion, scree test and parallel analysis all suggested three factors. The MAP test suggested four factors. The MAP test, scree test, and parallel analysis are all usually accurate within 1 factor (Zwick & Velicer, 1986; Velicer et al., 2000). This suggests that the PSI Scales most likely contain 3 or 4 factors. Previous researchers have found that parallel analysis is one of the most accurate methods of determining the number of factors (Ledesma, & Valero-Mora, 2007); therefore, additional weight was given to this test. Additionally, because the Kaiser-Guttman criterion typically overestimates the number of factors and this rule suggested three factors, it is less likely that our data contain the four factors indicated by the MAP Test (Cliff, 1988; Velicer, Eaton, & Fava, 2000). Therefore, three factors were extracted.

Several different rotations were examined: equamax, varimax, quartimax, direct oblimin (with delta .25, 0, -1, -15, and -30), and promax (with kappa 2, 3, and 4). Based upon the number of complex scales, the hyperplanar count, and the extent of correlation among the factors, the direct oblimin rotation with delta -1 was selected. It had the fewest number of complex scales (only four), a hyperplanar count of 21 (which was nearly the highest count), and moderate correlations among the factors (the average correlation was .29).

Results

Factor 1's four strongest loadings were for Recognizes Human Emotions, Adapts to Human Emotions, Predicts Human Emotions, and Predicts Human Cognitions. Factor 1 also had strong loadings for Recognizes Human Cognitions, and Adapts to Human Cognitions. Overall, Factor 1 seemed to be reflecting the perception of a mind. Factor 1 was therefore labeled Theory of Mind. For a numerical summary of each of the loadings for each factor see Table 3.

Factor 2 had three positive salient coefficients for Trustworthy, Helpful, Caring, and Friendly. These loadings suggest that Factor 2 was measuring the perception of a robots' social beneficence. Factor 2 also had three negative salient coefficients for Conceited, Hostile, and Rude, which suggests that factor 2 was reflecting the perception of a robots' humility and civility. Taken together, these suggest Factor 2 primarily reflects a quality of approachability. Factor 2 was therefore labeled Approachable Disposition.

Factor 3's loadings were highest for Recognizes Human Behaviors and Adapts to Human Behaviors. Additionally, there was a more moderate loading on Predicts Human Behaviors. These loadings suggest that Factor 3 primarily reflects recognizing, predicting, and adapting to human behaviors. Factor 3 was therefore labeled Reasoning about Behavior.

Table 3
Factor Analysis Results for Rotated Factors

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

Note. Salient factor pattern matrix coefficients > |0.3| are in bold face. h^2 = communality. No variables were reverse-scored for this analysis. Factor 1 = Theory of Mind. Factor 2 = Approachable Disposition. Factor 3 = Reasoning about Behavior.

Discussion

The purpose of this study was to examine the nature and number of factors that underlie PSI in robots. We used five criteria to determine the number of factors, and were surprised to find only three factors indicated rather than the four factors we hypothesized. The three factors found in this study were Theory of Mind, Approachable Disposition, and Reasoning about Behavior.

Theory of Mind reflects a robot's ability to recognize, predict, and adapt to the emotions and cognitions of humans. Approachable Disposition reflects the extent to which the robot was perceived as being friendly, trustworthy, caring, and helpful. Reasoning about Behavior reflects the ability to recognize, predict, and adapt to human behavior.

An understanding of the factors that underlie PSI in robots could help robot designers create more socially intelligent robots. For example, if a designer wanted to manipulate how approachable a robot was perceived to be, they would know that making the robot appear not conceited, not hostile, and not rude, as well as making the robot appear trustworthy, helpful, caring, and friendly are all important. These factors help to establish the interrelated patterns that likely exist within perceptions of robots. Knowing the patterns that influence the PSI is important because the more socially intelligent a robot is perceived to be, the more likely it will be able to accurately perform its intended tasks (Peters et al., 2017).

We expected to find four factors: social presentation, emotion, cognition, and behavior. We were surprised that we only found three factors. In our study, cognitions and emotions combined to form one factor instead of two separate factors. It could be that in our study, participants who viewed a robot as emotionally responsive also assumed the robot was predicting, recognizing, and adapting to cognitions. This, however, may or may not be a true reflection of the robots' actual capabilities or of people's perceptions of the robots' abilities. It could be that it is impossible for people to know if a robot can recognize or predict an emotion unless they see the robot adapting to that emotion. Therefore, if they see the robot adapting to an emotion, they might correctly note that it perceived the emotion. If they do not see the robot adapting to an emotion, they might (perhaps incorrectly) assume the robot did not perceive that emotion. Future research could use different robots to examine if different factors would be found. For example, in another study, researchers might include a robot that has just the ability to recognize and adapt to cognitions, but is without the ability to predict emotions.

Future studies could investigate how age, gender, and cultural differences might influence the number and nature of the factors. For example, researchers interested in designing effective robots for use in educational programs for children might be particularly interested in understanding how children perceive the social intelligence of robots. A further study of children's PSI of robots may result in the extraction of different factors, because children's perceptions and understanding of their own minds change as they develop (Flavell, 2004).

Gender might also influence the factors. This study surveyed both men and women but did not consider each gender independently. It is possible that a difference in one or more of the factors could exist if men and women perceive social intelligence differently. Ideally, future research should conduct separate analyses of men and women.

Furthermore, cultural norms might influence the factors. For example, a culture that highly values personal space might perceive the robots differently and this could affect the factors. Persons in a different culture may perceive the robot as more hostile and more rude rather than caring and friendly if the robot does not observe the cultural norms associated with personal space.

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