HUMAN-ROBOT INTERACTION

Measures of incentives and confidence in using a social robot

Nicole L. Robinson[1]*, Jennifer Connolly[2], Genevieve M. Johnson[3†], Yejee Kim[3†], Leanne Hides[4], David J. Kavanagh[2]

Measures of incentives and confidence in using a social robot were stable, predictive, and sensitive to changes in robot behaviors.

Rapid, recent advances in applications of social robots run the risk of exceeding potential users' willingness to engage with them. This highlights a need to assess factors that influence their acceptance and use (*1*). Current measures of users' perceptions typically assess a single psychological dimension (*2*), confound multiple constructs (*3*), assess global attitudes toward robots (*4*), and/or do not directly measure the level of social and emotional connection with social robots. To advance research in this area, an assessment measure that can quantify changes in social robot characteristics or behaviors and predict willingness to use social robots is required.

These new measures should have their basis in well-established psychological theory about the prediction of behavior. Two predictors have proved particularly powerful: self-efficacy (confidence in meeting current performance demands) and incentives (expectations about outcomes from an action) (*5*, *6*). Currently, we know of no published measure of self-efficacy or incentives about interpersonal interactions with a social robot. We developed and tested measures to fill this gap, examining their sensitivity to contrasting robot behaviors and their prediction of intentions to use a social robot.

Initial development of the measures involved administering them to groups of 202 female high school students who had observed an interaction with a NAO robot. Exploratory factor analyses indicated that the Robot Incentives Scale (RIS) had three subscales: emotional (liking or enjoyment of social robots), utility (whether they were useful or solved problems), and social/relational (their potential for social connection). The Robot Self-Efficacy Scale (RSES) had two subscales: operation (confidence in operating a social robot) and application (confidence in completing a task or goal with use of the robot). Intentions to use a social robot formed a single scale. The internal structures of the scales were confirmed in an online adult sample of 404 participants (Table 1), although the RSES required one item to be removed and errors on two pairs of similar items to be correlated before an acceptable fit was obtained. The internal consistencies of the subscales for all three scales were very high.

We tested whether the new scales were sensitive to more mechanical or humanoid behaviors from the NAO robot by using a student sample. The more humanoid robot received higher scores on all three measures but only when the students saw both types of behavior. The RIS and RSES subscales jointly predicted 78% of the variance in intentions to use the social robot in the student group. On their own, RIS subscales predicted 77% of the variance, whereas RSES subscales predicted only 40%. The adult group gave similar results, with RIS and RSES predicting 83% of the variance in intentions when used together (82 and 54% separately). In both groups, all RIS and RSES subscales except RSES operation contributed unique predictive variance.

In summary, the three scales provided a coherent and stable factor structure across the studies despite differences in the nature of the samples and observed interactions. However, the RSES required omission of one item to finalize an acceptable fit, suggesting a need for further replication. High internal consistencies of RSES and RIS subscales suggest a potential for shortening the length of assessment measures without affecting reliability. The measures were sensitive to comparisons of different social robot behaviors when individuals were able to contrast the behaviors. Because most participants had little prior exposure to robots, observations of the interactions were presumably dominated by their novelty. Future groups that have extensive experience with robotics or human-robot interactions may not need contrasting interactions to obtain differential ratings, because comparisons with previous experience would be available.

All RIS and RSES subscales made unique contributions to a concurrent prediction of intentions to use a social robot, except for RSES operation. However, almost all of the predictive power was from the RIS subscales, suggesting that assessments of incentives may be sufficient to predict intentions to use a robot for a social interaction. The limited prediction from self-efficacy was unexpected, because it is typically a stronger predictor of performance attainments than incentives (*6*). However, the focus of the intentions measure was on a social interaction rather than on controlling or programming the robot, making self-efficacy less relevant than incentives. If participants were required to undertake a more demanding role, then a different pattern of results may be obtained. As yet, we have not tested the ability of the measures to predict actual use of the robot. Generalization of results to other social robots, characteristics, and contexts also await determination. These studies provide strong initial support for the new measures, and the RIS may have wide potential application in assessing the acceptability of social robots.

SUPPLEMENTARY MATERIALS

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Text S1. Study design, materials, and methods.
Text S2. Exploratory factor analyses: Further notes.
Text S3. Comparisons of mechanical and humanoid robot behaviors.
Text S4. Confirmatory factor analysis.

[1]Australian Centre for Robotic Vision, Centre for Children's Health Research, Institute of Health and Biomedical Innovation and School of Psychology and Counselling, Queensland University of Technology, Brisbane, Australia. [2]Centre for Children's Health Research, Institute of Health and Biomedical Innovation and School of Psychology and Counselling, Queensland University of Technology, Brisbane, Australia. [3]Somerville House, Brisbane, Australia. [4]School of Psychology, The University of Queensland, Brisbane, Australia.
*Corresponding author. Email: n7.robinson@qut.edu.au
†These authors contributed equally to this work.

Table 1. The robot incentives scale, robot self-efficacy scale, and robot usage intention items. All items were rated on a 0 to 10 scale, with only end points labeled. RSES items are rated from "Sure I can't" to "Sure I can," and RIS and RUI items are rated from "Not at all" to "Definitely."

Robot Incentives Scale (RIS)	**Robot Self-Efficacy Scale (RSES)**	**Robot Usage Intention (RUI)**
	How confident are you that you can do the following with this robot:	If this robot were readily available…
Emotion	*Operation*	I would interact with this robot often
I like this robot	Use this robot	I would ask this robot for assistance
I would enjoy interacting with this robot	Control this robot	I would spend time with this robot
I would be happy to talk to this robot	Understand what this robot is saying	I would ask this robot to help me with a task on a regular basis
I would like to have this robot around me	Learn what to do with this robot	I would interact with this robot for a long time
This robot is entertaining	Work out what to do if this robot is not doing what I want it to do	
Utility	Communicate clearly with this robot	
This robot would be able to help solve problems	*Application*	
This robot would be useful for me to have in my life	Work with this robot to solve a problem	
This robot would be able to provide me with the things that I want from a robot	Work out what to do by talking to this robot	
This robot would provide reliable assistance to me	Get this robot to do something for me	
Social/Relational	Get this robot to help me with something	
I would open up easily to this robot	Make sure this robot does the task I set it	
I would talk to this robot about anything		
I would talk to this robot about things I could not talk about to my family or friends		

Text S5. Prediction of intentions from self-efficacy and incentives.
Fig. S1. Ratings of more mechanical and humanoid robot interactions.
Table S1. Results of exploratory factor analyses: Robot Incentives Scale (RIS).
Table S2. Results of exploratory factor analyses: Robot Self-Efficacy Scale (RSES).
Table S3. Results of exploratory factor analyses: Robot Usage Intention (RUI).
Table S4. Between-group differences on each subscale.
Table S5. Between-group differences on each subscale after the first robot observation.
Table S6. Time by condition results for each subscale.
Table S7. Results of confirmatory factor analyses.
Table S8. Multiple regressions predicting intentions from self-efficacy and incentives in the student sample.
Table S9. Multiple regressions predicting intentions from self-efficacy and incentives in the adult sample.
Data S1. Raw scores for scale development and experimental studies.
Reference (*7*)

REFERENCES AND NOTES

1. K. Dautenhahn, Socially intelligent robots: Dimensions of human–robot interaction. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **362**, 679–704 (2007).
2. R. E. Yagoda, D. J. Gillan, You want me to trust a ROBOT? The development of a human–robot interaction trust scale. *Int. J. Soc. Robot.* **4**, 235–248 (2012).
3. T. Nomura, T. Kanda, Rapport–expectation with a robot scale. *Int. J. Soc. Robot.* **8**, 21–30 (2016).
4. T. Nomura, T. Kanda, T. Suzuki, Experimental investigation into influence of negative attitudes toward robots on human-robot interaction. *AI Soc.* **20**, 138–150 (2006).
5. V. J. Strecher, B. M. DeVellis, M. H. Becker, I. M. Rosenstock, The role of self-efficacy in achieving health behavior change. *Health Educ. Q.* **13**, 73–92 (1986).
6. A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory* (Prentice-Hall Inc, 1986), pp. xiii+617.
7. A. Bandura, On the functional properties of perceived self-efficacy revisited. *J. Manage.* **38**, 9–44 (2011).

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