Cancer Genetic Counseling by Humanoid Robot: Modeling Multimodal Communication of Health Risk

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ABSTRACT

We describe the design and evaluation of a humanoid robot that explains inherited breast cancer genetics, and motivates women to obtain cancer genetic testing. The counseling dialogue is modeled after a human cancer genetic counselor, extended with data visualizations and nonverbal behavior. In a quasi-experimental pilot study, we demonstrated that interaction with the robot leads to significant increases in cancer genetics knowledge.

CCS CONCEPTS

Human-centered computing → Human computer interaction (HCI) → HCI design and evaluation methods

KEYWORDS

Human robot interaction; user studies; social robots; genetic counseling; risk communication; health education

ACM Reference format:

Shuo Zhou, Prasanth Murali, Meghan Underhill-Blazey, and Timothy Bickmore. 2020. Cancer Genetic Counseling by Humanoid Robot: Modeling Multimodal Communication of Health Risk. In *Proceedings of 2020 ACM/IEEE International Conference on Human-Robot Interaction (HRI'20 Companion), March 23-26, 2020, Cambridge, United Kingdom.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3371382.3378303

1 Introduction

Several studies have now demonstrated the efficacy of humanoid robots as well as virtual agents to deliver health education and counseling across a range of topics [1], with robots successfully promoting rehabilitation exercise [2], diet [3], and physical activity [4], and virtual agents successfully used to promote several additional health behaviors [5–8]. This work aims to explore the efficacy of health counseling by humanoid robots in complex domains such as cancer genetics. To the best of our knowledge, this is the first work attempting to provide genetic counseling using a robot.

Individuals with a personal or familial cancer history that indicates potential inherited risks are usually recommended genetic counseling and testing, to guide potential cancer screening and treatments. Despite being standard of care, it is estimated that only about 50% or less of at-risk individuals obtain genetic counseling or testing due to a variety of personal or system level factors [9–12]. To further complicate the clinical context, information regarding genetic risk is often difficult to understand, and may be misinterpreted, leading to inappropriate decision-making and ineffective family communication [13]. Automation of genetic counseling is particularly important given the current shortage of genetic counselors in the US [14].

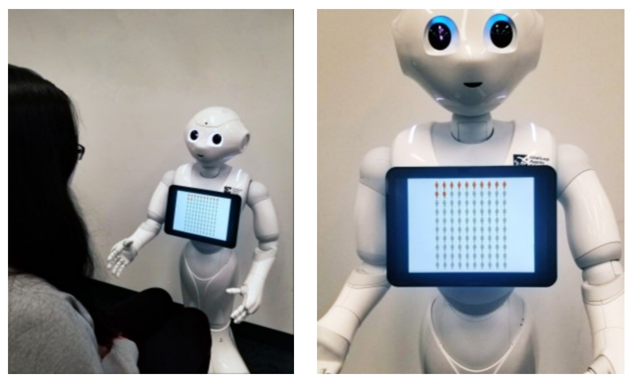

Figure 1: Robot Genetic Counselor explaining a 12% risk using a pictograph, showing 12 highlighted humans out of a hundred.

Communicating genetic risks is an important component of genetic counseling [15], and involves providing a large amount of numerical or statistical information [16]. During a typical genetic counseling session, patients are presented with information in a variety of formats, including relative and absolute risks, probabilities, frequencies, verbal risk descriptions, and possible health outcomes. This quantitative information is communicated verbally, nonverbally (e.g., via metaphoric hand gestures [17]), and/or through the use of data visualizations [18]. For example, pictographs or frequency diagrams are used to convey statistical risk information [19, 20], bar graphs are used in making multiple comparisons and depicting relative risks [20, 21], histograms and

HRI '20 Companion, March 23–26, 2020, Cambridge, United Kingdom

ACM ISBN 978-1-4503-7057-8/20/03.
https://doi.org/10.1145/3371382.3378303

pie charts are used to emphasize part-to-whole concepts such as percentages [18, 21], and scatter plots are used to display variability [18, 21].

We are developing and evaluating a robotic genetic counselor using the Pepper platform [22] (Figure 1). Pepper has ideal affordances for health counseling, given its speech generation and recognition ability, articulate humanoid arms and hands for conversational hand gestures [17], and its integrated LCD screen that can be used to display data visualizations of risk, frequencies, and other numeric information.

2 System Design and Implementation

We videotaped a counseling session between a human genetic counselor and a mock breast cancer patient at a comprehensive cancer center in the northeastern United States. The audio from the session was transcribed, analyzed and partitioned into discourse segments [23], translated into a hierarchical transition network dialogue formalism, and extended with frequently asked questions (that could be asked by users) and comprehension tests (asked of the user by the robot) to ensure understanding of key concepts. Additional data visualization graphics were created to accompany the counseling language, particularly in support of quantitative information and concepts, following the empirical literature on risk communication [18]. The final dialogue was implemented for Pepper using SoftBank's Choreographe, using Pepper's automatically-generated hand gestures and highly constrained user speech input to advance the dialogue.

3 Methods

We conducted a quasi-experimental pilot study to evaluate the acceptance of receiving breast cancer genetic education from a robot, and the robot's ability to increase user comprehension of breast cancer genetics. Participants were required to be English-speaking, female, 18 years of age or older, and were primarily recruited from a university campus to interact with the robot in a single 25-min counseling session. The study was approved by our university IRB and participants were compensated for their time.

3.1 Measures

3.1.1 Breast Cancer Genetics Knowledge. The primary outcome measure was participant knowledge of breast cancer genetics, assessed using an 11-item true-false scale, modified based on the knowledge scale validated in [24, 25]. Each item was scored as 1 if the participant answered correctly, and 0 if answered incorrectly or left blank. Participants' knowledge was assessed immediately before and after their interaction with the robot counselor.

3.1.2 Self-Report Scales. Participants' experience with the robot was measured using a series of 7-point single-item scales (Table 1). Genetic testing intention was assessed before and after the interaction using a single-item scale used in [25]: at the present time, which of the following statements describes you best? (1. not considering genetic testing. / haven't thought about it. 2. considering genetic testing. 3. probably will have genetic testing. 4. definitely will have genetic testing.)

4 Results

Ten women completed the study, aged 20.8 on average (sd=2.6), all college students. Overall, participants were satisfied with the robot and the counseling experience (Table 1).

Table 1: Acceptance of and Satisfaction with Robot. Single-item scale measures. Anchors: 1='not at all' to 7='very much' except where noted. Single sample Wilcoxon signed rank tests demonstrating scores significantly above neutral.

Single-Item Scale Outcomes	mean (SD)	p-value
How satisfied were you with Pepper?	5.1 (1.0)	.01*
How satisfied were you with the entire experience?	6.0 (1.2)	<.01*
How much did you like Pepper?	6.1 (1.0)	<.01*
How much did you trust Pepper?	5.8 (1.0)	<.01*
How knowledgeable was Pepper?	6.8 (0.4)	<.01*
How much information did you get? (1=too little; 4=just right; 7=too much)	4.2 (0.9)	n.s.
How likely would you make a commitment to follow the recommended guidelines for breast cancer screening?	6.1 (0.7)	<.01*
How likely would you be willing to talk more about your breast cancer risks with your primary care doctor or a genetic counselor?	6.4 (0.8)	<.01*

Participants' post-treatment scores for breast cancer genetics knowledge (mean=10.0, sd=1.5) significantly increased compared with their pre-treatment scores (mean=7.8, sd=1.1), paired t(9)=-3.8, p<.01.

Participants' post-treatment ratings for intent to obtain genetic testing (median="considering genetic testing") was significantly greater compared with their pre-treatment ratings (median="not considering genetic testing / haven't thought about it"), paired Wilcoxon signed rank test, p=.01.

In post-session interviews, participants indicated that they liked receiving information through multiple modalities. The data visualizations, in particular, were "*good for a visual learner*" (P9) and made the concepts "*easier to understand*" (P7).

5 Conclusion & Future Work

We found that participants were comfortable learning about breast cancer genetics from a robot, and found the robot knowledgeable and trustworthy. Importantly, their interaction with the robotic genetic counselor led to a significant increase in their understanding of breast cancer genetics, as well as a significant increase in their intent to obtain genetic testing.

For future work, we are studying the ability of Pepper to communicate quantitative information and risk concepts using metaphoric hand gestures, and plan to develop a framework that will automatically generate descriptions of these concepts using a combination of speech, hand gesture, and data visualizations.

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